



A review of models for near-field exposure pathways of chemicals in consumer products

Huang, Lei; Ernstoff, Alexi; Fantke, Peter; Csiszar, Susan A.; Jolliet, Olivier

Published in:
Science of the Total Environment

Link to article, DOI:
[10.1016/j.scitotenv.2016.06.118](https://doi.org/10.1016/j.scitotenv.2016.06.118)

Publication date:
2017

Document Version
Peer reviewed version

[Link back to DTU Orbit](#)

Citation (APA):
Huang, L., Ernstoff, A., Fantke, P., Csiszar, S. A., & Jolliet, O. (2017). A review of models for near-field exposure pathways of chemicals in consumer products. *Science of the Total Environment*, 574, 1182-1208.
<https://doi.org/10.1016/j.scitotenv.2016.06.118>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

A review of models for near-field exposure pathways of chemicals in consumer products

Lei Huang^{1*}, Alexi Ernstoff², Peter Fantke², Susan A. Csiszar³ and Olivier Jolliet¹

¹Environmental Health Sciences & Risk Science Center, School of Public Health, University of Michigan, Ann Arbor, Michigan, 48109-2029, United States

²Quantitative Sustainability Assessment Division, Department of Management Engineering, Technical University of Denmark, 2808 Kgs. Lyngby, Denmark

³Oak Ridge Institute for Science and Education Research Participant, at the US Environmental Protection Agency, National Risk Management Research Laboratory, Cincinnati, OH, 45268, USA

*Corresponding author

Phone: +1 (734) 389-9681; E-mail: huanglei@umich.edu

Abstract

Exposure to chemicals in consumer products has been gaining increasing attention, with multiple studies showing that near-field exposures from products is high compared to far-field exposures. Regarding the numerous chemical-product combinations, there is a need for an overarching review of models able to quantify the multiple transfers of chemicals from products used near-field to humans. The present review therefore aims at an in-depth overview of modeling approaches for near-field chemical release and human exposure pathways associated with consumer products. It focuses on lower-tier, mechanistic models suitable for life cycle assessments (LCA), chemical alternative assessment (CAA) and high-throughput screening risk assessment (HTS). Chemicals in a product enter the near-field via a defined “compartment of entry”, are transformed or transferred to adjacent compartments, and eventually end in a “human receptor compartment”. We first focus on models of physical mass transfers **from** the product to ‘near-field’ compartments. For transfers of chemicals from article interior, adequate modeling of in-article diffusion and of partitioning between article surface and air/skin/food is key. Modeling volatilization and subsequent transfer to the outdoor is crucial for transfers of chemicals used in the inner space of appliances, on object surfaces or directly emitted to indoor air. For transfers from skin surface, models need to reflect the competition between dermal permeation, volatilization and fraction washed-off. We then focus on transfers from the ‘near-field’ to ‘human’ compartments, defined as respiratory tract, gastrointestinal tract and epidermis, for which good estimates of air concentrations, non-dietary ingestion parameters and skin permeation are essential, respectively. We critically characterize for each exposure pathway the ability of models to estimate near-field transfers and to best inform LCA, CAA and HTS, summarizing the main characteristics of the potentially best-suited models. This review identifies large knowledge gaps for several near-field pathways and suggests research needs and future directions.

Keywords

Human exposure models, high-throughput risk screening, life cycle impact assessment, mass transfer fractions, consumer products, indoor environment

Contents

Abstract	2
Keywords	2
1. Introduction	4
2. Review procedure and criteria	6
2.1 Overview of near-field, far-field and human compartments	6
2.2 Review scope and evaluation criteria for model applicability for LCA, CAA and HTS	8
3. Model review for chemical release processes	9
3.1 Transfers of chemicals from article interior	9
3.1.1 Transfer from article interior to indoor and near-person air	9
3.1.2 Transfer from article interior into food and beverages	14

53	3.1.3 Transfer from article interior to skin surface	17
54	3.1.4 Transfer from article interior to object surfaces	20
55	3.2 Transfers of chemicals from the inner space of an appliance	20
56	3.2.1 Transfer from appliance inner space to indoor and near-person air.....	20
57	3.2.2 Transfer from appliance inner space to object surfaces	24
58	3.3 Transfers of chemicals from object surfaces	25
59	3.3.1 Transfer from object surfaces to indoor and near-person air	25
60	3.3.2 Transfer from object surfaces to skin surface	28
61	3.4 Transfers of chemicals from skin surface	30
62	3.4.1 Transfer from skin surface to air	30
63	3.5 Transfers of chemicals from indoor and near-person air	32
64	3.5.1 Transfer of chemicals in sprays	32
65	3.5.2 Indoor transport and fate processes	34
66	4. Model review for human exposure processes	37
67	4.1 Transfer to respiratory tract.....	37
68	4.2 Transfer to gastrointestinal tract	38
69	4.2.1 Dietary ingestion	38
70	4.2.2 Non-dietary ingestion	39
71	4.3 Transfer to epidermis.....	42
72	5. Summary and recommendation	45
73	Acknowledgements	47
74	References	48

75
76
77

1. Introduction

Collectively, the products we use in our daily lives contain thousands of chemicals (Judson et al., 2009) and new chemical-product combinations are continuously introduced into commerce. Each product has the potential to expose people to chemicals, through using the product and through environmental emissions along a product's life cycle (e.g. from manufacturing). The manner of a product's use and its physical properties (e.g. if solid, liquid, or spray), as well as the properties of the chemicals therein (e.g. vapor pressure) are important factors in determining the fate of and exposures to chemicals within consumer products. For example, some products are intended for use as indoor sprays (e.g. air fresheners) or indoor fixtures (e.g. furniture), or are meant to be directly ingested (e.g. food) or applied to the skin (e.g. skin care products). The multitude of potential uses of products on today's market, and the diversity of chemicals used therein, lead to various chemical exposure magnitudes, durations, pathways, and pose a significant research challenge with respect to quantifying and comparing product-related exposures.

The need for incorporating human exposure information into chemical prioritization has been well identified (Gangwal et al., 2012; Swanson et al., 1997; Wambaugh et al., 2013). Traditionally, physiochemical properties such as vapor pressure, Kow and environmental half-lives of chemicals have been used to rank potentials for human exposures (Gangwal et al., 2012; Swanson et al., 1997; Wambaugh et al., 2013). However, these methods can not reflect well the interaction between various chemical properties that occur for multiple exposure pathways (Wambaugh et al., 2013). Also, the exposure estimates based on these simple properties do not correlate well with monitoring-based estimates of exposures (Gangwal et al., 2012; Wambaugh et al., 2013). Therefore, the use of models, instead of using chemical properties as proxy, is preferred to make estimates of human exposures for chemical prioritization or ranking purposes (Wambaugh et al., 2013).

Improved information on human exposure to a vast array of chemicals in various product applications is needed for several qualitative or quantitative science-policy oriented tools, including life cycle assessment (LCA) (Jolliet and Fantke, 2015), chemical alternatives assessment (CAA) (Lavoie et al., 2010), and risk-based high-throughput screening (HTS) (Dionisio et al., 2015; Shin et al., 2015a; Wetmore et al., 2015). LCA is a product-oriented environmental assessment methodology which characterizes potential exposure to thousands of chemicals using semi-automated modeling approaches, such as multimedia mass-balance box models. Exposure assessments in LCA use an intake fraction (iF)-based approach, for which further details can be found in [SI Section S2](#). Most of the current LCA modeling approaches focus on population exposures related to environmental emissions occurring throughout a product's life cycle, so called "far-field exposure pathways", but do not consider consumer and population exposure to chemicals in consumer products associated with product use, i.e., "near-field exposure pathways" (Jolliet et al., 2015). Exposure to chemicals in consumer products has been however gaining increasing attention in the LCA context, with first attempts to consider exposure to consumer products focusing on indoor air modeling (Hellweg et al., 2009; Wenger et al., 2012) and cosmetics (Ernstoff et al., 2016). These studies demonstrated that exposures resulting from indoor or near-field chemical releases can often be substantially higher than exposures resulting from environmental or far-field emissions (Jolliet et al., 2015; Liagkouridis et al., 2014; Lorber, 2007; Rosenbaum et al., 2015). Such approaches now need to be systematically extended to model exposures to chemicals in other consumer products such as multiple types of household detergents (for e.g. window cleaning, dishwashing and washing machines) and chemicals encapsulated in articles and in food packaging. Critical for LCA is the use of mass-balance based approaches ensuring conservation of mass and avoiding conservative estimates.

CAA focuses on screening alternatives to hazardous chemicals in consumer products (Lavoie et al., 2010). Current CAA frameworks usually lack quantitative exposure estimates (Jacobs et al., 2015) and mostly fail to integrate near- and far-field exposures although this is considered important (NRC, 2014). This renders it difficult to fully understand and incorporate exposure patterns in CAA (Fantke et al., 2015). There is therefore a need to review and identify which quantitative models could be suitable for screening assessment within the CAA framework, reflecting exposure mechanisms while being easily applicable. CAA needs are very similar to LCA, e.g. in terms of comparative rather than conservative assessments or ability to consistently address multiple impact categories.

Risk-based HTS is another promising approach to address the challenge of assessing multiple exposures with limited empirical data and resources available. Several recent HTS initiatives focus on semi-automated methods to screen thousands of chemicals for potential exposure magnitudes (Wetmore et al., 2015), incorporating both far-field and near-field exposures (Wambaugh et al., 2013). Three main HT modeling frameworks spanning multiple consumer product types and chemicals have been developed to evaluate exposures for screening and prioritization of chemicals in consumer products, SHEDS-HT (Isaacs et al., 2014), Consexpo (Delmaar et al., 2005) and an ExpoDat program Tier I framework (Shin et al., 2015b). While several scenarios for product-chemical specific exposures (e.g., direct inhalation of tobacco smoke, dermal application of skin care products) have been modeled somewhat elaborately within these frameworks, other scenarios are treated with very simple models/assumptions or are simply neglected. For example, ExpoDat Tier 1 (Shin et al., 2015b) assumes a 10% transfer of chemicals from food contact materials into food, from products placed within the mouth into the saliva, and from solid objects to indoor air, and these pathways are not at all considered in SHEDS-HT (Isaacs et al., 2014). Consexpo and SHEDS-HT provide interesting ways to classify chemical-product combination and exposure parameters, but they often rely on simplified or conservative assumptions rather than mass-balance based modeling for certain exposure pathways.

To define the best possible starting point for improving current LCA, CAA and HTS exposure assessment frameworks, the present review aims to provide an in-depth overview of the existing modeling approaches of near-field chemical release and human exposure pathways associated with the use of consumer products. We first propose a compartmental structure for products in the near-field environment, define the review scope and the evaluation criteria for model applicability for LCA, CAA and HTS (Section 2). We then structure this review around two key aspects for modeling exposure to chemicals in consumer products: quantifying the chemical mass leaving a product, for example through passive diffusion from inside a solid object (e.g. furniture) and release into indoor air or dermal contact and transfer onto the skin surface; and quantifying the subsequent chemical fate and transport, and human exposure pathways and routes, such as inhalation, direct ingestion, dermal absorption and hand-to-mouth contact. The chemical release processes will be reviewed from an emitter perspective (i.e., from the chemical source origin), and are grouped in Section 3. It should be noted that following an emitter perspective a chemical source originating in the near-field can often also lead to emissions to the far-field environment. While the far-field exposure pathways and potential ecosystem damages are not a focus of this review, the link between near-field and far-field models is of particular relevance in LCA and CAA. Thus, we also briefly mention cases where models have explicitly linked near-field sources to outdoor emissions. Once a chemical process or pathway arrives at the human body interface, it is reviewed from a receptor perspective and grouped in Section 4. Within this review we aim to summarize available models to estimate each of these processes, as well as to identify areas requiring further research. Furthermore, to support LCA, CAA and HTS as important emerging methodologies for impact and risk mitigation applied to the countless product-chemical combinations on the market, we provide a

critical indication how exposure models could best inform these methods. Our goal is to provide a reference to support future LCA, CAA and HTS modeling frameworks to more holistically and consistently quantify exposure to chemicals in consumer products.

2. Review procedure and criteria

To support the progress of modeling exposure to chemicals in consumer products we structured this review around quantifying steps along each consumer product exposure pathway which we define by transfers connecting a series of adjacent compartments (Figure 1). A near-field exposure pathway begins when a chemical in a product enters the near-field via a defined “compartment of entry”, then may be transferred to adjacent compartments or transformed within a compartment, and eventually ends in a “human receptor compartment” as the exposure interface between the near-field environment and the human body. Compartmental chemical fate, transport, and exposure modeling relies on simplifying and subdividing the environment into different media (compartment) that have homogeneously distributed physical properties, such as flow rates in water bodies. Compartmental multimedia models have been widely used for the far-field environment (Mackay, 2010; Rosenbaum et al., 2008), but have not been presented specifically for multiple product-chemical combinations in the near-field environment (for details see SI Section S3). Below we define potentially relevant compartments for modeling exposure to consumer product chemicals (Section 2.1) and evaluation criteria for the models required to estimate compartmental fate and transfers in LCA, CAA and HTS contexts (Section 2.2).

2.1 Overview of near-field, far-field and human compartments

In this review we differentiate the environment into three sets of compartments (Figure 1), any of which may be a compartment of entry and/or an intermediate compartment for chemicals within a given exposure pathway. These sets are a) near-field compartments that encompass any indoor or near-product user medium or environment within close proximity of humans during professional or consumer product use, b) far-field compartments that encompass any outdoor medium or environment that is not in close proximity to humans during product use, and c) human receptor compartments which encompass the human body and represent the exposure interfaces, through ingestion (gastrointestinal tract), inhalation (respiratory tract), and dermal permeation (epidermis). We acknowledge that some consumer products may also be used in the outdoor environment (e.g. insect repellents), and such circumstances are special cases of near-field outdoor exposures. Chemicals may exchange between and amongst the near-field and far-field environmental compartments and be further transferred to human body compartments.

Chemical mass exchanges between adjacent compartments are referred to as transfers (arrows in Figure 1) and occur through various processes ranging from passive diffusion to active ventilation which require respective modeling approaches as identified in Section 3. As the focus of this review, near-field exposures refer to exposure pathways beginning with a near-field or human compartment of entry and any transfer occurring only between near-field compartments before the final human receptor compartment, e.g. volatilization from an object surface (compartment of entry) to indoor air (intermediate compartment) and finally to the human respiratory tract (human receptor compartment). Near-field exposures can have interactions with far-field exposures, which is discussed in SI Section S4.

We identified six major near-field compartments relevant to modeling the exposure pathways to chemicals in consumer products, including article interior, inner space of an appliance, food and

beverages, object surface, the skin surface, and indoor and near-person air—the latter four can have direct transfers to the human body as demonstrated in **Figure 1**. The definition of each near-field compartment is presented in **Table 1**. Each compartment can consist of several phases, which may include gaseous, solid, liquid or semi-liquid phases. Dust is considered as the solid (particulate) phase in each relevant compartment, such as object surface, skin surface and indoor air. Each of these six compartments can be a compartment of entry or an intermediate compartment, depending on the specific product and use scenario considered. The present review focuses on the transfers among these six compartments and between these six and the three human receptor compartments, as depicted in **Figure 1**, acknowledging that the modeling of near field exposure could be extended to additional compartments or transfer pathways.

Table 1. Definition of near-field compartments

Compartment	Definition
Article interior	The bulk matrix of a solid object or material. This compartment is for chemicals that are encapsulated within a product material or incorporated into the material matrix, such as flame retardants within furniture or plasticizers within vinyl flooring and food contact materials.
Inner space of an appliance	The space enclosed within an appliance that has a controlled interface with indoor air, and that has its content (air or water) to be drained or ventilated outdoors after operation. Examples include detergents, disinfectants, or softeners used in appliances such as dishwashers, washing machines, or clothes dryers. Other enclosed appliances such as microwaves, ovens, closets, computer cases and storage boxes do not belong to this compartment since it is assumed releases from such items occur directly and completely indoors.
Skin surface	A conceptual space between the top surface of the skin and the indoor air, which can include different phases such as liquid, semi-solid (gel) and solid (particles). This is a distinct compartment from the epidermis because chemicals in contact with the skin surface may partition into the air, or remain on the skin surface and therefore be subject to removal (e.g. via wash-off), or may be transferred into the epidermal receptor compartment as the final compartment for an exposure pathway.
Indoor and near-person air	The air in an enclosed indoor space within which a human may be situated, for example a room or shower stall.
Object surface	A conceptual space between the top surface of an object and the indoor air, which can include different phases such as liquid, semi-solid (gel) and solid (particles). Examples include cleaning solutions applied on the floor surface, and dust particles on the surface of a desk.
Food and beverages	Edible products intended for human ingestion.

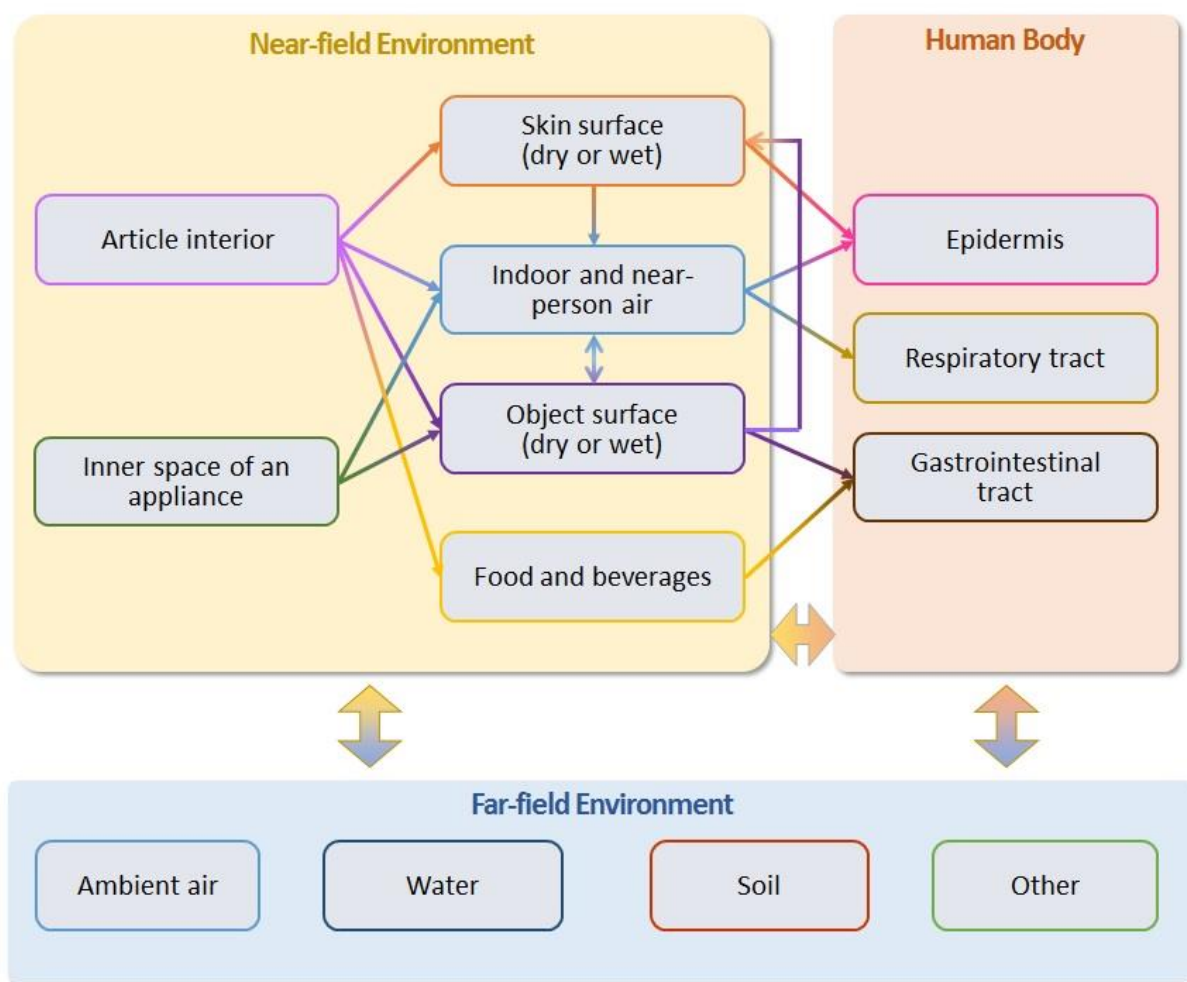


Figure 1. Links between the near-field environment, the far-field environment, and the human body. This review focuses on models that quantify the transfers between and amongst the near-field environment and human body compartments. Line arrows represent inter-compartmental transfers that are addressed in the present review.

2.2 Review scope and evaluation criteria for model applicability for LCA, CAA and HTS

We reviewed a variety of models that can be used to estimate the inter-compartmental transfers indicated in Figure 1. Within each model review section (Sections 3 and 4), we first aim to provide a basic summary of all relevant modeling approaches from simple to more complex, and then evaluate the applicability for LCA, CAA and HTS of the modeling approaches according to criteria defined in this section. While the tables in Sections 3 and 4 aim to provide a compact overview of existing models for the individual exposure-related transfers and pathways, the suitability of models for use in LCA, CAA and HTS is further summarized and contrasted in Table 11 in Section 5.

Modeling approaches are typically empirical or mechanistic of which both can vary in complexity, accuracy, and applicability. Empirical models use regressions to fit parameters within predefined mathematical equations (such as an exponential decay) to experimental data. Empirical models are often difficult to generalize across types of chemical-product combinations and environmental configurations (e.g. room volume, temperature). In contrast, mechanistic models are based on the

underlying physicochemical mechanisms such as volatility and molecular diffusion processes, which are easier to generalize across chemicals and situations. This review focuses on mechanistic models because they are more suitable to apply across chemical classes, product types, and environmental configurations. We also describe methods available to estimate the key model input parameters, including quantitative structure–activity relationships (QSARs) which are generalizable across chemicals.

After reviewing all the existing models for a single pathway, the applicability of these models for LCA, CAA and HTS will then be evaluated qualitatively. In terms of applicability, the models will be evaluated analyzing main strengths and weaknesses in four aspects: (1) the ability to account for the product and chemical characteristics relevant for the considered pathway; (2) the validity of the main assumptions; (3) the availability of analytical solutions, the model complexity, and its ability to easily handle large datasets and (4) the availability of methods to estimate the key input parameters for a large number of chemicals. The relative importance of each of these criteria needs to be determined by the actual users depending on their own study scope and objectives. It should be noted that model complexity is often strongly related to the model accuracy; decreased model complexity usually comes with loss of model accuracy (though not necessarily), which is mentioned in the review and a balance between complexity and accuracy will need to be determined by the actual practitioners.

3. Model review for chemical release processes

3.1 Transfers of chemicals from article interior

Examples of chemical-product combinations with the “article interior” compartment of entry include various volatile organic compounds (VOCs) in building materials, phthalates in plastics, and polybrominated diphenyl ethers (PBDEs) in furniture and electronics. These chemicals can constitute a major emission source in the indoor environment (Little et al., 1994; Little et al., 2012; Watkins et al., 2011; Xu and Little, 2006). Depending on physicochemical properties of the chemical and the product matrix and on the manner of product use (e.g. handled manually or used as food packaging), inter-compartmental transfers of chemicals in article interior mainly occur as direct partitioning to indoor air (Section 3.1.1), food (Section 3.1.2) or skin surface lipids (Section 3.1.3), or as releases of particulates to the object surface (Section 3.1.4).

3.1.1 Transfer from article interior to indoor and near-person air

Existing models

When modeling the chemical transfer from article interior to indoor or near-person air, two types of processes are involved: the release of chemicals from article interior to the gas phase of indoor air, and the removal of chemicals from the gas phase of indoor air. In a mass balance of the indoor air, the former process represents the source, while the latter represents the removal processes. Since these two types of processes are interrelated, they need to be considered together to form a complete model system. Table 2 lists various options for these processes instead of complete models one by one, because different combinations of these processes can result in a large number of actual models which are not suitable to be listed.

For the source (i.e., chemical release from article interior), most existing models consider that it is driven by the chemical’s internal diffusion within the article, which can be described by the Fick’s 2nd Law (Eq. 3.1-1) (Deng and Kim, 2004; Huang and Haghighat, 2002; Kumar and Little, 2003b; Little et al., 1994). Initial conditions and boundary conditions need to be specified to solve the Fick’s 2nd Law, which is a partial differential equation. Initial conditions specify the initial chemical concentration inside the object,

while boundary conditions specify the interactions at the object material-air interface. There are different initial and boundary conditions representing different types of products, product materials and indoor environment configurations (Table 2), and the researchers need to select the “right” equations according to their own modeling needs.

In terms of initial conditions, most models assume an initial uniform distribution of a chemical within the object (Deng and Kim, 2004; Huang and Haghighat, 2002; Little et al., 1994) (Eq. 3.1-2a), while others describe a non-uniform initial distribution (Kumar and Little, 2003b; Xu and Zhang, 2004) (Eq. 3.1-2b).

Regarding boundary conditions, typically three conditions need to be specified. The first condition describes mass transfer resistance at the object material (abbreviated as “material” below)-air interface. In earlier models it is assumed that release is controlled by internal diffusion (Eq. 3.1-3a) (Kumar and Little, 2003b; Little et al., 1994), where in more recent models it is assumed that release is driven by the concentration gradient between the air layer adjacent to the material surface (boundary-layer) and the bulk air, which is controlled by convective mass transfer (Eq. 3.1-3b) (Deng and Kim, 2004; Huang and Haghighat, 2002; Yang et al., 2001b). The second boundary condition is about the material-boundary layer interface, where most models assume that the chemical concentration in boundary-layer air is in equilibrium with the concentration at the material surface (Eq. 3.1-4). As a third boundary condition, the base (bottom) of the object is assumed to be either impervious (Deng and Kim, 2004; Huang and Haghighat, 2002; Little et al., 1994) with zero mass flux (Eq. 3.1-5a), or pervious (Wang et al., 2006) like the top surface (Eq. 3.1-5b).

Removal processes generally include the sorption effects of indoor surfaces and the sorption to particles. For indoor releases, sorption to surfaces such as walls and ceilings can be important mass sinks. For example, semi-volatile organic compounds (SVOCs), such as flame retardants and phthalates, have very low vapor pressures and tend to partition strongly onto interior surfaces (Liu et al., 2013). The surface sorption rate can be determined by the convective mass-transfer through an air-material boundary layer (Liu et al., 2013) (Eq. 3.1-6). The surface and the boundary-layer air are generally assumed to be in equilibrium, which can be assumed linear (Eq. 3.1-7a) (Liu et al., 2013; Yang et al., 2001a) or nonlinear (Freundlich isotherm, Eq. 3.1-7b) (Xu and Little, 2006). In addition to sorption onto indoor surfaces, sorption to airborne particles also needs to be considered for SVOCs, since SVOCs are expected to mainly partition into the particulate phase in air (Xu and Little, 2006). Sorption to airborne particles will decrease the SVOC concentration in the gas phase, which can increase the concentration gradient between the boundary-layer air and the bulk air and thus enhance SVOC emissions from the material (Xu and Little, 2006). Xu and Little (Xu and Little, 2006), for example, have assumed a linear instantaneously reversible equilibrium relationship between the particle-bound SVOCs fractions and the gas-phase SVOCs fractions (Eq. 3.1-8).

After setting up the relevant source and removal processes, a mass balance equation is needed to combine these processes. If the indoor air is assumed to be well-mixed, the mass balance can be represented by Eq. 3.1-9 (Xu and Little, 2006). The fourth and fifth terms on the right-side of Eq. 3.1-9 describe the losses due to adsorption onto interior surfaces and airborne particles, while the last term describes the removal of particles by ventilation. Note that the last three terms may be left out if the sorption effects are considered negligible, e.g., typically for VOCs. The completed mass balance equation can be solved for the concentration in the indoor air, $C_g(t)$, and the concentrations inside the material, $C_m(x,t)$. The emission rate $G_{ma}(t)$ can then be derived using Eq. 3.1-3, and the integration of $G_{ma}(t)$ over time gives the total mass emitted to the indoor air. Several more complex models did not make the assumption of well-mixed air (Deng and Kim, 2007; Yang et al., 2001a; Yang et al., 2001b). Instead,

computational fluid dynamics (CFD) were used to describe the indoor air flow leading to relatively complex solutions less suited for HTS purposes.

For most SVOCs present as additives in solid objects, their initial concentrations in the object are relatively high, but the release of the SVOCs from the object occurs so slowly that the SVOC concentrations in the object can be assumed constant (Little et al., 2012; Liu et al., 2013; Xu et al., 2012). Using this assumption, the model system described above can be greatly simplified, as there is no need to solve the partial differential equation (Eq. 3.1-1). In addition, for screening purposes, steady-state can be assumed for the indoor air to further simplify the calculations, i.e., letting the left side of Eq. 3.1-9 equals zero (Little et al., 2012). A solution for this simplified gas-phase SVOC concentration can be given by Eq. 3.1-10 (Little et al., 2012). However, this solution assumes steady-state which does not always apply, and it ignores the SVOC sorption and subsequent diffusion into indoor surfaces.

One extension for the models described above is to consider multi-layer source materials. The Fick's 2nd Law equation (Eq. 3.1-1) describes only the internal diffusion of chemicals in a single-layer solid material. In reality many building materials are multi-layer composites. For example, carpets are typically comprised of fibers backed with a layer of polymer and wood products are comprised of a top layer of paints, coatings and/or sealants (Yuan et al., 2007). Thus, several studies have extended the single-layer model to a multi-layer system (Deng et al., 2010; Hu et al., 2007; Kumar and Little, 2003a; Wang and Zhang, 2011; Yuan et al., 2007; Zhang and Niu, 2004). The basic governing equation for multi-layer systems also follows Fick's 2nd Law (Eq. 3.1-1). The major assumptions are that all material layers are in perfect contact with each other, and equilibrium exists at every interface between adjacent layers. Thus, the flux from layer i to the interface between layer i and adjacent layer $i+1$ equals the flux from the interface to layer $i+1$, and the concentrations in these two adjacent layers can be expressed as a partition coefficient. These governing equations can be combined with the various boundary and initial conditions discussed above to constitute a complete mass balance system which can be solved analytically or numerically.

Other extensions of the single-layer model are models for porous materials. Gypsum, wood chipboard, concrete and brick are example materials that have macropores ($d > 50$ nm) and do not behave as homogenous solids (Blondeau et al., 2003). A porous material consists of pores (air) and solid regions, and chemicals such as VOC/SVOCs can be present both within the pore space (gas-phase) and on the solid surface (Lee et al., 2005). Chemicals can also be present in the solid phase (particle-bound phase) (Liu et al., 2013). The governing equation of one-dimensional diffusion within the porous material can thereby be expressed as a sum of gas and solid phase diffusions (Xiong et al., 2008)(Eq. 3.1-11). A linear or nonlinear equilibrium relationship using a partition coefficient can be assumed between the pores and the solid phase (Haghighat et al., 2005; Lee et al., 2005; Liu et al., 2013; Xiong et al., 2008). A linear equilibrium is generally assumed for situations where chemical concentrations in indoor air are much lower than the saturation concentrations (Haghighat et al., 2005; Lee et al., 2005). For the boundary condition at the material surface, it is assumed that the pores at the surface and the adjacent air are connected, so the concentration in the pores is equal to the concentration in the boundary-layer air (Haghighat et al., 2005; Lee et al., 2006; Lee et al., 2005; Liu et al., 2013; Xiong et al., 2008). Diffusion equations for porous materials are similar to those for the solid materials, although additional parameters such as porosity and diffusion coefficients for the pore space are needed. Thus, a multi-phase model may be simplified to simulate a homogeneous solid material if the diffusion coefficient is modified to take into account pore space diffusion. Furthermore, Haghighat et al. (Haghighat et al., 2005) have demonstrated that the single-phase and multi-phase models are interchangeable, and the impact

373 of porosity is negligible if the material porosity (fraction of air in the material, unitless) is more than one
 374 order of magnitude smaller than the chemical's solid-phase/gas-phase partition coefficient (unitless).

375

376 Table 2. Equations to model the transfers of chemicals from article interior to indoor air

Source: chemicals in article interior

I. Fick's 2nd Law of diffusion within the article material

$$\frac{\partial C_m(x,t)}{\partial t} = D_m \cdot \frac{\partial^2 C_m(x,t)}{\partial x^2} \quad (3.1-1)$$

II. Initial conditions for Fick's 2nd Law

(1) Initial concentration in the material

(1.1) Uniform

$$C_m(x, 0) = C_{m0} \quad \text{for } 0 \leq x \leq L \quad (3.1-2a)$$

(1.2) Non-uniform

$$C_m(x, 0) = C_{m0}(x) \quad \text{for } 0 \leq x \leq L \quad (3.1-2b)$$

III. Boundary conditions for Fick's 2nd Law

(1) Convective mass transfer resistance

(1.1) Gas-phase resistance neglected

$$G_{ma}(t) = -D_m \cdot \frac{\partial C_m(x,t)}{\partial x} (x = L) \quad (3.1-3a)$$

(1.2) Gas-phase resistance considered

$$G_{ma}(t) = -D_m \cdot \frac{\partial C_m(x,t)}{\partial x} (x = L) = h_m(C_{gmb}(t) - C_g(t)) \quad (3.1-3b)$$

(2) Equilibrium at the material-air interface

$$K_{ma} = \frac{C_m(L,t)}{C_{gmb}(t)} \quad (3.1-4)$$

(3) Base of the material

(3.1) Impervious

$$\frac{\partial C_m(x,t)}{\partial x} (x = 0) = 0 \quad (3.1-5a)$$

(3.2) Pervious

$$-D_m \cdot \frac{\partial C_m(x,t)}{\partial x} (x = 0) = h_{m,base}(C_{gmb,base}(t) - C_g(t)) \quad (3.1-5b)$$

Removal processes

I. Sink/sorption effect of indoor surfaces

(1) Sorption rate of indoor surfaces

$$\frac{dSC_{ssurf}(t)}{dt} = h_s(C_g(t) - C_{gsb}(t)) \quad (3.1-6)$$

(2) Equilibrium at the indoor surface-air interface

(2.1) Linear equilibrium

$$SC_{ssurf}(t) = K_{sa} C_{gsb}(t) \quad (3.1-7a)$$

(2.2) Nonlinear equilibrium

$$SC_{ssurf}(t) = K_{sa} C_{gsb}(t)^n \quad (3.1-7b)$$

II. Sorption to airborne particles

$$C_p(t) = K_{pa} \cdot C_g(t) \cdot C_{TSP} \quad (3.1-8)$$

Air mass balance equation

$$V \frac{dC_g}{dt} = Q \cdot C_{gin}(t) - D_m \cdot \frac{\partial C_m(x,t)}{\partial x} (x=L) \cdot A_m - Q \cdot C_g(t) - \frac{dSC_{ssurf}(t)}{dt} \cdot A_s - \frac{dC_p(t)}{dt} \cdot V - Q \cdot C_p(t) \quad (3.1-9)$$

Simplified, steady-state solution for SVOCs

$$C_g = \frac{h_m \cdot C_{gmb} \cdot A_m}{h_m \cdot A_m + (1 + K_{pa} \cdot C_{TSP}) \cdot Q} \quad (3.1-10)$$

Extension of Fick's 2nd Law: porous materials

$$\varepsilon \cdot \frac{\partial C_{mpore}}{\partial t} + (1 - \varepsilon) \cdot \frac{\partial C_{msolid}}{\partial t} = D_{mpore} \cdot \frac{\partial^2 C_{mpore}}{\partial x^2} + D_{msolid} \cdot \frac{\partial^2 C_{msolid}}{\partial x^2} \quad (3.1-11)$$

$C_m(x, t)$ - chemical concentration in the source material ($\mu\text{g}/\text{m}^3$), t - time (s), x - linear distance from the bottom of the source material (m), D_m - diffusion coefficient of the chemical in the source material (m^2/s), $G_{ma}(t)$ - emission rate from the source material ($\mu\text{g}/\text{s}$), L - material thickness (m), h_m - convective mass transfer coefficient at the source material surface (m/s), $C_g(t)$ - gas-phase chemical concentration in the bulk air ($\mu\text{g}/\text{m}^3$), $C_{gmb}(t)$ - gas-phase chemical concentration in the boundary-layer air adjacent to the source material ($\mu\text{g}/\text{m}^3$), $C_{mo}(x)$ - distribution of initial chemical concentration inside the source material ($\mu\text{g}/\text{m}^3$), $SC_{ssurf}(t)$ - chemical concentration on the interior sorption surface ($\mu\text{g}/\text{m}^2$), h_s - convective mass transfer coefficient at the sorption surface (m/s), $C_{gsb}(t)$ - gas-phase chemical concentration in the boundary-layer air adjacent to the sorption surface ($\mu\text{g}/\text{m}^3$), $C_p(t)$ - particle phase chemical concentration ($\mu\text{g}/\text{m}^3$), K_{pa} - the particle-air partition coefficient (m^3/kg), C_{TSP} - concentration of total suspended particles in air (kg/m^3), V - room volume (m^3), Q - room ventilation rate (m^3/s), A_m - surface area of the emission source material (m^2), A_s - surface area of interior surfaces (m^2), ε - fractional porosity (unitless).

Key parameters and data availability

The key parameters primarily include the material-phase diffusion coefficient D_m , the material/air partition coefficient K_{ma} , and the convective mass-transfer coefficient h_m . D_m and K_{ma} are both chemical- and product-specific parameters. They can be measured experimentally or predicted using correlations with physicochemical properties and product properties. The experimental methods for determining D_m and K_{ma} for VOCs have been reviewed extensively by Liu et al. (Liu et al., 2013). Various correlation methods for estimating D_m and K_{ma} have also been reviewed by Guo (Guo, 2002) and Holmgren et al. (Holmgren et al., 2012), which predict the values of D_m and K_{ma} mainly as functions of vapor pressure, molecular weight, molar volume, Abraham solvation parameters and the type of product material. These empirical correlations generally require fitting coefficients corresponding to specific types of materials and compound groups, which limit their application to less studied materials or compound groups.

The convective mass-transfer coefficient h_m is a chemical- and system-specific parameter, i.e., it depends on both the chemical properties and the conditions of the near-field environment. h_m is usually

predicted by empirical correlations rather than determined experimentally. The correlation most commonly employed is established by several dimensionless numbers, including Sherwood number (Sh), Reynolds number (Re) and Schmidt number (Sc) (Liu et al., 2013). Holmgren et al. presented another method to estimate h_m from the chemical's diffusivity in air, air velocity, air viscosity and air density (Holmgren et al., 2012). Several earlier correlations for estimating h_m have been reviewed by Guo (Guo, 2002).

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, the main strengths of the current diffusion models are that they are mechanistic and can account for different product and chemical characteristics, such as pervious/impervious base, uniform/non-uniform initial concentration, sink/sorption effects and particles. However, the model complexity and parameter availability are major concerns regarding usefulness in LCA and HTS. For example, the most complex model configurations rely on numerical solution techniques or CFD simulations, which require specialized software, are time-consuming and are not easily generalized to different conditions. Even for the simplest model setup which assumes uniform initial concentration in the material (Eq. 3.1-2a), impervious material base (Eq. 3.1-5a), equilibrium at the material-air interface (Eq. 3.1-4), and neglects convective mass transfer resistance (Eq. 3.1-3a), the analytical solution includes solving for the positive roots to a transcendental equation, which can only be achieved numerically, unless retrieved from a table. Because there are infinite roots of the transcendental equation, the resulting analytical solutions are composed of the sum of an infinite series which may require at least 5000 terms to minimize the truncation error, while in certain cases even 10000 terms are not enough to minimize the truncation error (Huang and Jolliet, 2015). Therefore, the existing model solutions would pose a considerable computational burden to the LCA or HTS user. For easier application in LCA and HTS, the analytical solutions may have to be simplified. As mentioned above, simplified solutions exist for SVOCs, but such solutions assume steady-state which is not always appropriate, and they ignore the SVOC sorption and subsequent diffusion into indoor surfaces. We recently proposed a simplified model for VOCs which decouples the material and air by assuming a pseudo-steady-state condition between emission and loss; this model uses two exponentials and all explicit equations to predict the emissions, which is much simpler than the original model and shows potential for application in HTS (Huang and Jolliet, 2015). In terms of the availability of key parameters, experimental data for D_m and K_{ma} exist for limited number of chemicals, and QSARs are only available for specific types of materials and chemical classes, which would also limit their application to hundreds of chemicals in HTS analysis. More generic QSAR models need to be developed to estimate these parameters.

3.1.2 Transfer from article interior into food and beverages

Existing models

Chemicals within food contact materials (FCM) are special cases of chemicals in article interior. Chemicals within FCM may migrate into food products. Food may come in contact with various materials e.g. during production, preparation, and consumption but the main focus within the literature are migration models intended for packaging materials which are intended to be in direct contact with foods. Poças et al. (Poças et al., 2008) for example reviewed FCM migration modeling methods up until 2008, which tend to focus on regulatory compliance testing for polymeric packaging materials (i.e. plastic). Since that time, there have been limited advancements, for example extending modeling methods for other packaging types (e.g. paper and board composites) (Zülch and Piringer, 2010), and other

applications (e.g. population-scale assessments of dietary exposure to bisphenol A from FCM) (Oldring et al., 2014).

The most common modeling approach for exposure to chemicals in FCM via food are based on the same principle as the diffusion model for chemicals within a solid object where the transient diffusion through the material is given by the Fick's 2nd Law (Eq. 3.1-1). This modeling approach is also used by regulators within the European Union and the United States (Begley et al., 2005). The specified initial conditions assume homogenous distribution of the chemical migrant within the FCM and the initial concentration of the migrant in the FCM-contacted food is set to zero (Poças et al., 2008). For boundary conditions, it is assumed that no transfer with air at the outer surface of the material, and no mass transfer resistance within food at the food/packaging interface. The migration process is controlled by the diffusion through the packaging material and the migrant is assumed to be evenly distributed in the food. A solution for this model system was given by Crank (Crank, 1975), which is now commonly known as the Piringer model (Poças et al., 2008). The Piringer model is well described in several papers (Begley et al., 2005; Poças et al., 2008) and EU regulatory documents (Simoneau, 2010) (Eq 3.1-12). Similar to the diffusion model discussed in Section 3.1.1, the Piringer model requires iterative numerical solutions of the tangential transcendental route equation.

The main assumption (i.e. a boundary condition) that the concentration of the chemical is instantaneously well-mixed in the food is likely only valid for fluid foods, albeit when the concentration in the food remains small in comparison to the concentration in the package, or the diffusion through the food is rapid, this assumption may still be useful for predictive modeling. Further work on these issues (e.g. as outlined by Poças et al. (Poças et al., 2008)) is needed; however, because empirical work is often performed with a liquid simulant, obtaining sufficient empirical data to validate such a model poses a challenge.

Boundary conditions that are more complex may better describe the migration process. For example, the mass transfer resistance at the food/packaging interface can be approximated by a convective process using a convective mass transfer coefficient (h_m) (Poças et al., 2008), which is similar to the diffusion model described in Section 3.1.1.

Generally, very few migration models exist that are not based on Fickian diffusion (Poças et al., 2008); for example Poças et al. suggested an approach based on the Weibull kinetic model (Pocas et al., 2012) (Eq 3.1-13). For the limited chemical-material combinations studied, the Weibull modeling approach correlates well with other proposed methods based on Fick's 2nd Law (Pocas et al., 2012).

Table 3. Equations to model the transfer of chemicals from FCM to food and beverages

Piringer model	
$\frac{m_f(t)}{m_f(\infty)} = 1 - \sum_{n=1}^{\infty} \frac{2\alpha(1+\alpha)}{1+\alpha+\alpha^2 q_n^2} \exp(-D_p t \frac{q_n^2}{L^2})$	(3.1-12a)
$\alpha = \frac{V_f}{K_{pf} V_p}$	(3.1-12b)
q_n are the positive roots of: $\tan(q_n) = -\alpha \cdot q_n$	(3.1-12c)
Weibull kinetic model	

$$\frac{C_f(t) - C_f(\infty)}{C_f(0) - C_f(\infty)} = \exp[-(t/\gamma)^\beta] \quad (3.1-13)$$

Key parameter: D_p

$$D_p^* = 10^4 \cdot \exp\left(A_p - 0.1351MW_c^{\frac{2}{3}} + 0.003MW_c - \frac{10454}{T}\right) (cm^2 s^{-1}) \quad (3.1-14a)$$

$$\text{with } A_p = A_p' - \frac{\tau}{T} \quad (3.1-14b)$$

A_p' - "Upper-bound" material-specific diffusion parameter (unitless), $C_f(0)$ - initial concentration in the food ($\mu g/m^3$), $C_f(t)$ - concentration of migrant in the food at time t ($\mu g/m^3$), $C_f(\infty)$ - concentration in the food at equilibrium ($\mu g/m^3$), D_p - diffusion coefficient in the package (m^2/s), D_p^* - upper-bound diffusion coefficient for a specific polymer (m^2/s), K_{pf} - package-food partition coefficient (unitless), L - thickness of the package (m), MW_c - chemical's molecular weight (g/mol), $m_f(t)$ - mass of chemical present in the food at time t (μg), $m_f(\infty)$ - mass of chemical present in the food at equilibrium (μg), T - absolute temperature (K), V_f - volume of food (m^3), V_p - volume of package used (m^3), γ - scale parameter (unitless), β - shape parameter (unitless), τ - material specific diffusion parameter.

Key parameters and data availability

The key parameters to evaluate the Piring model and most Fickian-based solutions are the diffusion coefficient D_p of the migrant through the FCM, and the partition coefficient between the FCM and the food K_{pf} (Begley et al., 2005; Poças et al., 2008), both of which are chemical- and product-specific. For D_p , a model specifically applicable for polymers (i.e. plastics) is often applied (Eq 3.1-14), which requires two material specific diffusion parameters, A_p' and τ . Values for A_p' and τ have been empirically derived for various polymer types (Begley et al., 2005). Zülch & Piring (Zülch and Piring, 2010) also presented modifications of Eq. 3.1-14a for paper and board materials, where A_p was replaced with a semi-empirical term $10+A_B$, where A_B is a board-specific parameter added to the $A_p=10$ for LDPE as reference. A_B is derived the same way as A_p (Eq. 3.1-14b) for paper and board.

The partition coefficient between the polymer (or any other material) and the food, K_{pf} , influences the solutions to the tangential root equation within the Piring model. Difficult to obtain experimentally, K_{pf} poses a particular challenge for migration modeling and thereby is typically set to 1 (most common) or 1000 (for lipophilic substances in contact with aqueous foods, i.e. water or water-based beverages) (Begley et al., 2005; Poças et al., 2008; Simoneau, 2010). Interestingly, setting the partition coefficient to 1 is often incorrectly referred to as being a worst-case assumption—empirical evidence and understanding of the partition coefficient K_{pf} (which is the ratio of concentration in FCM and concentration in food) clearly demonstrates a partition coefficient far lower than 1 is possible and would correspond more to a worst-case scenario (Ozak et al., 2010; Poças et al., 2008). Few methods exist to estimate K_{pf} which varies according to the migrant's lipophilicity, the packaging matrix, and the polarity of the food (simulant) in question (i.e. ethanol-equivalency or oil). Due to analytical constraints, modeling methods for FCMs are often parameterized or evaluated against migration experiments with food simulants (not actual foods), which represent the polarity of food items and are typically composed of ethanol-water mixtures or natural oils (e.g. olive oil) (Poças et al., 2008). For example, Ozak et al. performed empirical experiments necessary to present a linear correlation method as a function of the octanol-water partition coefficient of the migrant and ethanol equivalency of food simulants (Ozak et al., 2010). They provided linear correlations for 10, 50, 95% ethanol-equivalencies and for olive oil. One of the objectives of the FACET project (Flavours, Additives and food Contact material Exposure Task) (Oldring et al., 2014) was to expand this approach and develop methods to estimate K_{pf} for a wider range of ethanol food simulants. However, the results of this work (Seiler et al., 2014) are only

summarized in a figure, whereas the data or linear correlations required for modeling have to our knowledge neither been made available via Seiler et al. (Seiler et al., 2014) nor via the FACET software. An additional challenge identified and addressed within the FACET project (Oldring et al., 2014) is to assign the appropriate ethanol equivalency for various food items, for example according to their fat content or texture (Seiler et al., 2014).

Other parameters are relatively easily measurable in comparison to D_p and K_{pf} , including the thickness of the product, the density, phase composition and volume of food, contact surface area, contact temperatures and contact duration, all of which are product- or system-specific. When running such models within regulatory compliance testing, constant default values are often assumed for these parameters (Simoneau, 2010; USFDA, 2007).

For the Weibull kinetic model (Eq. 3.1-13), there are two key parameters. The scale parameter γ is chemical- and product-specific, which is based on the diffusion coefficient of the migrant and the material thickness, while the shape parameter β is material-specific and is estimated based on empirical values (Pocas et al., 2012).

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, the Piringer model (Eq. 3.1-12) is mechanistic and can account for characteristics of the FCM product, the food that is packaged, as well as the chemical migrant. However, its assumption of instantaneous even distribution of the migrant in the food may only be valid for liquid foods and limited circumstances of solid foods. In addition, the Piringer model requires numerical solutions which are relatively complex. Data availability is another concern for the Piringer model, as only limited empirical correlations are available to predict D_p and K_{pf} . The FACET software (Oldring et al., 2014), which aims to provide a modeling framework for exposure to a multitude of chemicals within foods, also bases exposure due to migration on the Piringer model; however, estimates are only available for a limited number of FCM chemicals within the software, which may be indicative of the difficulty of applying such a model for HTS. Operationalizing the use of the Piringer model for LCA and HTS in a spreadsheet software and developing more generalizable QSARs or similar approaches to estimate D_p and K_{pf} , would make the modeling approach more suitable for LCA and HTS purposes. On the other hand, the Weibull approach (Pocas et al., 2012) is based on a simple exponential, but the obvious downside of this approach is that it is an empirical model which has only been evaluated based on a limited number of empirical data; hence, it cannot be applied/generalized to conditions that have not been evaluated. This model also relies on material-specific empirical values which are difficult to obtain and thereby must be estimated or fixed. This makes the Weibull approach not suitable for LCA and HTS unless a modeling approach becomes available to estimate β , the shape parameter. When chemical specific data are not available, then the availability of a readily usable model and estimation of its parameters (in this case the diffusion and partitioning coefficients) are likewise barriers to performing a CAA. Thus if chemicals considered in the CAA have similar K_{ow} and MW , then similar migration will be estimated by the proposed models and only toxicity will determine prioritization.

3.1.3 Transfer from article interior to skin surface

Existing models

Chemicals within article interior can directly partition into skin-surface lipids while an article is in contact with the skin. Example scenarios include hand contact with desks, crawling on the floor and wearing clothes with direct skin contact. Such transfers have been ignored in several near-field exposure

assessment frameworks (Glen et al., 2012; Isaacs et al., 2014; Shin et al., 2015b), and a very limited number of models is available to describe the underlying transfer processes.

One simple model is the migration rate approach, which uses the migration rate of the chemical from products to skin surface in a unit of $\mu\text{g}/\text{m}^2/\text{s}$ (Eq. 3.1-15a). The US Consumer Product Safety Commission and the European Chemicals Bureau use this approach to assess the dermal contact exposure to several phthalates (DEHP, DINP, DBP) in a variety of products (e.g., toys, crib bumpers and playpen) (CPSC, 2010; ECB, 2008). ConsExpo employs the same principle for its dermal migration model but replaces the migration rate and contact surface area with the leachable fraction of chemical ($\text{g}/\text{g}/\text{s}$) and the amount of product in contact with skin (g), respectively (Eq. 3.1-15b) (Delmaar et al., 2005).

Several other approaches directly relate the chemical's concentration in product to the dermal contact exposure. The European Centre for Ecotoxicology and Toxicology of Chemicals (ECETOC) has developed a targeted risk assessment (TRA) modeling tool to assist in first tier assessments of consumer exposure. in the ECETOC TRA it is assumed that only the chemical in a small layer of the object can be transferred to the skin (ECHA, 2010) (Eq. 3.1-16). A similar approach is also employed by EPA's Consumer Exposure Model (CEM), version 1.3 (USEPA, 2015).

In contrast, Delmaar et al. suggested another approach which uses the diffusion distance instead of an arbitrary layer thickness. They adopted the widely used diffusion model for the release of chemicals within article interior (Delmaar et al., 2013), which describes the diffusion of a chemical in the product by the Fick's 2nd law, and the diffusive flux out of the product at the product surface by the Fick's 1st law, as reviewed in section 3.1.1. The amount transferred onto the skin can then be calculated by multiplying the diffusive flux with the skin contact area. Delmaar et al. also provided a simplified version of this method, which utilizes the average diffusion distance L_{diff} and where it is assumed that all the chemical in a layer with thickness L_{diff} will diffuse out from the product and expose the skin (Delmaar et al., 2013) (Eqs. 3.1-17a & 17b).

Table 4. Equations to model the transfer of chemicals within a solid object to skin surface

Migration rate approach	
(1) CPSC format	
	$m_{o_ss} = J_{o_ss} \times A_{o_ss} \times t_{derm} \quad (3.1-15a)$
(2) ConsExpo format	
	$m_{o_ss} = f_{o_ss} \times M_{o_ss} \times t_{derm} \quad (3.1-15b)$
Limited layer approach: ECETOC TRA	
	$m_{o_ss} = C_m \times A_{o_ss} \times L_{o_ss} \times N_{o_ss} \quad (3.1-16)$
Simplified diffusion approach: Delmaar et al.	
	$m_{o_ss} = C_{m0} \times A_{o_ss} \times L_{diff} \quad (3.1-17a)$
	$L_{diff} = \sqrt{2 \times D_m \times t_{derm}} \quad (3.1-17b)$

A_{o_ss} - surface area of the skin contacted (m^2/event), C_m - chemical concentration in the product ($\mu\text{g}/\text{m}^3$), C_{m0} - initial chemical concentration in the product ($\mu\text{g}/\text{m}^3$), D_m - diffusion coefficient of the chemical in the product (m^2/s), f_{o_ss} - leachable fraction, which is the amount of chemical that migrates to the skin surface per unit amount of product ($\text{g}/\text{g}-\text{s}$), M_{o_ss} - mass of product in

contact with skin, m_{o_ss} - chemical mass that is transferred from within the object to the skin surface (μg), N_{o_ss} - number of object-to-skin contact events (unitless), J_{o_ss} - migration rate of the chemical from products to skin surface ($\mu\text{g}/\text{m}^2\text{-s}$), L_{o_ss} is the thickness of the layer from which the chemical is assumed to be released (m), L_{diff} - average distance a diffusing molecule will travel in a material during a given time period (m), t_{derm} - dermal contact duration (s).

Key parameters and data availability

Several system-specific parameters are common across different models for estimating the transfer from article interior to skin surface, such as the skin contact area A_{os} and the contact duration t_{derm} or number of contacts N_{os} , which can be obtained from the exposure factors handbook (USEPA, 2011) and the object use pattern. Other than these common parameters, the different models described above require very diverse input parameters.

For the migration rate approach (Eq. 3.1-15), the migration rate J_{o_ss} of the chemical from products to skin surface is the key parameter, with a unit of $\mu\text{g}/\text{m}^2\text{-s}$. J_{o_ss} is both chemical- and product-specific, and is typically measured. Only few studies have been conducted to measure the migration rates of phthalates from various consumer products during skin contact (e.g., touching, pressing, scrubbing) (CPSC, 2010; Özer and Güçer, 2012). Api et al. measured the transfer rate ($\mu\text{g}/\text{cm}^2$ per grasp) of three fragrances (cinnamic aldehyde, eugenol, d-Limonene) from candles to human hands (Api et al., 2007). It is found that the migration rate of phthalates was not directly correlated to the phthalate concentrations in the products (CPSC, 2010; Niino et al., 2003), suggesting that the migration rate may not be predicted from the chemical concentration in the product, and there is no clear mathematical relationship that relates the migration rate to other specific properties, which would limit its use for LCA, CAA and HTS.

For the limited layer approach employed by ECETOC TRA (Eq. 3.1-16), the most important parameter is the layer thickness L_{os} , which is a product-specific parameter and determines the mass of chemical that can be released from within a solid object. ECETOC TRA provides default values of either 100 or 10 μm for L_{os} depending on the product category (ECHA, 2010). However, these default values were chosen solely based on expert judgment and were not supported by any scientific data (ECHA, 2010), which limits the use of this approach in comparative assessment contexts like LCA where such product property data might drive differences in assessment results.

For the diffusion model approach proposed by Delmaar et al. (Eqs. 3.1-17a & b), the key parameter is the material-phase diffusion coefficient D_m (Delmaar et al., 2013). As reviewed in Section 3.1.1, D_m depends on both chemical- and product-properties, and can be measured experimentally or predicted using empirical correlations (Guo, 2002; Holmgren et al., 2012; Liu et al., 2013).

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, the migration rate approach is simple, but it requires the migration rate which needs to be measured, since no mathematical relationships are available to predict this parameter. Thus, it is difficult to apply this model to chemical-product combinations with no experimental data for migration rates. The limited layer approach is also simple, but it requires the layer thickness currently provided as a generic estimate mainly based on expert judgment, which will lead to increased uncertainty since the layer thickness is in fact product-specific. Thus, this approach is only useful for obtaining low tier rough exposure estimates such as HTS, and is not suitable for comparative assessment contexts like LCA and CAA. The diffusion approaches by Delmaar et al. (Delmaar et al., 2013) consider the internal diffusion, which accounts for the characteristics of the chemical inside a product.

However, in these models it is assumed that every chemical molecule that is able to diffuse to the product surface will be further transferred to the skin surface, which unrealistically ignores the partitioning between the material surface and the skin and the mass-transfer resistance. Therefore, the diffusion-based approaches would lead to overestimates of the transfer to skin surface, and would be more suitable as a worst-case estimate. Thus, development of a more accurate model with predicted parameters is needed. A possible direction may be to start from the diffusion model discussed in section 3.1.1, and use a partition coefficient to relate the model-derived chemical concentration on product surface to the concentration on skin surface.

3.1.4 Transfer from article interior to object surfaces

Studies have suggested that chemicals within article interior can be transferred to dust particles on the object surface via direct partitioning, or via physical processes such as abrasion (Liagkouridis et al., 2014; Webster et al., 2009). Dust partitioning or abrasion may be more important chemical release processes than diffusion for chemicals with very low volatility such as PBDEs (Liagkouridis et al., 2014). However, no modeling methods were identified to account for these mechanisms for estimating related exposure. Liagkouridis et al. (Liagkouridis et al., 2014) suggested that testing methods for abrasion resistance of materials may be used to support the modeling of abrasion. Several studies have reported the results of wear and abrasion testing for carpets and upholstery fabrics (Pourdeyhimi et al., 1994; Warfield and Slaten, 1989), but they generally provided data regarding strength, elongation and fractal dimension rather than weight loss of the bulk material. A possible direction to modeling chemical-specific abrasion could be to estimate the fraction of bulk material lost through time as surface dust, and thus more data on the weight loss of bulk material will be needed through abrasion testing. For the direct partitioning, a simple equilibrium relationship using a partition coefficient may be assumed between the chemical concentration in the object and the chemical concentration in dust particles, but methods need to be developed to measure or estimate the partition coefficients for a wide range of chemical-product combinations in order to become useful for LCA, CAA and HTS approaches.

3.2 Transfers of chemicals from the inner space of an appliance

Near-field releases of chemicals used in appliances can occur through air exchange between the appliance and the indoor air (Section 3.2.1); and chemicals can also be retained on the surface of the items within the appliance, such as clothes or dishes (Section 3.2.2). While the compartment of entry “inner space of an appliance” can include various appliances such as dishwashers, washing machines, dryers, refrigerators, etc., we have focused our review on models for dishwashers and washing machines with which major use of detergents are associated.

3.2.1 Transfer from appliance inner space to indoor and near-person air

Existing models

The US EPA Exposure and Fate Assessment Screening Tool (EFAST) Consumer Exposure Module (CEM) (USEPA, 2007) provides a screening-level model to evaluate the air emissions of VOCs in liquid detergents used in washing machines. It assumes that 90% of the applied VOC will be volatilized at a constant rate (Eq. 3.2-1a). The time required for 90% of the VOC to volatilize is estimated from the VOC’s molecular weight and vapor pressure (Eq. 3.2-1b). Two restrictions are applied to this model to improve its predictions (USEPA, 2007): (1) the vapor concentration derived from the emission rate

cannot exceed the chemicals' saturation concentration in air; and (2) if exposure duration is longer than the user-specified duration of use, then the model stops the air emission and the remaining chemical mass is assumed to be discharged down the drain.

The EPA IAQX program (Simulation Tool Kit for Indoor Air Quality and Inhalation Exposure) also provides three models (Models 12, 51 & 52) that are able to predict the volatilization of chemicals from an indoor aqueous solution. Model 12 is similar to the EFAST-CEM model as a constant emission rate is assumed (McCready et al., 2012), but it further relies on the assumption that the VOC concentration in the headspace of the washer is in equilibrium with its water concentration (Eqs 3.2-2a & 2b). Alternatively, in models 51 & 52 it is assumed that the emission is driven by the concentration gradient between the liquid product phase and the indoor air, which will decrease over time (McCready, 2013). In model 51 it is assumed that the process is limited by the liquid-phase mass transfer (Eq. 3.2-3), while model 52 considers the limitation from the gas-phase mass transfer (Eq. 3.2-4) (McCready, 2013).

The above models do not truly account for the enclosed nature of washing machines, as the water inside the washing machine is simulated as fully connected to the indoor air. Howard and Corsi (Howard-Reed et al., 1999; Howard and Corsi, 1998) thus developed a two-phase mass balance model to more accurately describe the emission process from enclosed devices. The inside of the enclosed appliance is assumed to consist of a liquid phase and a gas phase (headspace). For the wash/rinse cycle of a washing machine or a dishwasher, the liquid phase may be treated as a batch reactor (Eq. 3.2-5a), and the gas phase can be assumed to approach a continuous-flow, well-mixed reactor (Eq. 3.2-5b).

Assuming that the volumes of both liquid and gas phases remain constant during operation and that the initial concentration of the considered chemicals in indoor air is negligible for this emission source, analytical solutions can be obtained (Howard-Reed et al., 1999). At the end of appliance operation, the model assumes that the residual chemical retained in the headspace would be released to the indoor air as an instantaneous "puff" if the washing machine or dishwasher is opened soon after operation (Howard-Reed et al., 1999). Moreover, if a dynamic equilibrium is achieved between the liquid and gas phases within the appliance the solution may be further simplified. In this case, the chemical concentrations in the two phases will be related by Henry's Law (Howard-Reed et al., 1999). For this simplified model, Howard-Reed et al. (Howard-Reed et al., 1999) proposed to use a numerical solution with very small time steps (<10 s) to predict the mass release rate over time, since the total chemical mass within the appliance is not constant due to e.g. headspace ventilation. The time needed to reach equilibrium would be relatively short for systems with low headspace ventilation rates and high products of mass transfer coefficients and surface area ($\phi_{liq_all}A_{vol}$). Experiments using a residential dishwasher demonstrated that the equilibrium will be achieved after 1-2 min of dishwasher operation (Howard-Reed et al., 1999).

The fill cycle of a washing machine needs to be investigated independently. During the fill cycle, water is entering the machine and is accumulating in the washing machine basin, so the input of chemical from the inlet water needs to be accounted for (Eq. 3.2-6a). If the inlet water does not contain the chemical of interest (e.g., chemical is only present in the detergent), then equation (3.2-6a) becomes the same as equation (3.2-5a). The mass balance of the headspace for the fill cycle (Eq. 3.2-6b) is the same as that for the wash/rinse cycle (Eq. 3.2-5b). However, for the fill cycle, the volumes of the liquid phase and the headspace are both changing with time, for which numerical solutions are needed (Howard and Corsi, 1998).

717 Table 5. Equations to model the transfer of chemicals enclosed within an appliance to indoor air

EFAST-CEM model	
$G_{ha} = f_w \cdot M \cdot 10^6 / t_{vol90}$	(3.2-1a)
$t_{vol90} = 3600 \cdot 145 / (MW_c \cdot P_V \cdot \frac{760}{101325})^{0.9546}$	(3.2-1b)
IAQX models	
(1) Model 12	
$C_{eahs} = H \cdot C_{eaw} / (R \cdot T)$	(3.2-2a)
$G_{ha} = C_{eahs} \cdot Q_{eahs}$	(3.2-2b)
(2) Model 51	
$G_{ha} = A_{vol} \cdot \phi_{liq_all} \cdot (C_{eaw} - C_g / K_{aw})$	(3.2-3)
(3) Model 52	
$G_{ha} = A_{vol} \cdot \phi_{gas_all} \cdot (K_{aw} \cdot C_{eaw} - C_g)$	(3.2-4)
Mass balance model (wash/rinse cycle of a washing machine or a dishwasher)	
$\frac{dC_{eaw}V_{eaw}}{dt} = -\phi_{liq_all}A_{vol} \left(C_{eaw} - \frac{C_{eahs}}{K_{aw}} \right)$	(3.2-5a)
$\frac{dC_{eahs}V_{eahs}}{dt} = Q_{eahs}C_{gin} - Q_{eahs}C_{eahs} + \phi_{liq_all}A_{vol} \left(C_{eaw} - \frac{C_{eahs}}{K_{aw}} \right)$	(3.2-5b)
Mass balance model (fill cycle of a washing machine)	
$\frac{dC_{eaw}V_{eaw}}{dt} = Q_{eaw}C_{win} - \phi_{liq_all}A_{vol} \left(C_{eaw} - \frac{C_{eahs}}{K_{aw}} \right)$	(3.2-6a)
$\frac{dC_{eahs}V_{eahs}}{dt} = Q_{eahs}C_{gin} - Q_{eahs}C_{eahs} + \phi_{liq_all}A_{vol} \left(C_{eaw} - \frac{C_{eahs}}{K_{aw}} \right)$	(3.2-6b)
Proposed simplified mass balance model to facilitate HT analysis	
$\frac{dC_{eahs}(t) \cdot V_{eahs}}{dt} = -Q_{eahs} \cdot C_{eahs}(t)$	(3.2-7a)
$C_{eaw}(t) = \frac{C_{eahs}(t)}{K_{aw}}$	(3.2-7b)
$C_{eahs}(t) \cdot V_{eahs} + C_{eaw}(t) \cdot V_{eaw} = M \text{ for } t = 0$	(3.2-7c)
Key parameters: overall mass transfer coefficients	
$\frac{1}{\phi_{liq_all}} = \frac{1}{\phi_{liq}} + \frac{1}{\phi_{gas} \cdot K_{aw}}$	(3.2-8a)
$\frac{1}{\phi_{gas_all}} = \frac{1}{\phi_{gas}} + \frac{K_{aw}}{\phi_{liq}}$	(3.2-8b)

718 A_{vol} - surface area of the liquid pool (m^2), C_{eaw} - chemical concentration in the liquid phase ($\mu g/m^3$), C_{eahs} - chemical
719 concentration in the headspace air ($\mu g/m^3$), C_g - chemical concentration in room air ($\mu g/m^3$), C_{gin} - gas-phase chemical
720 concentration in the inflow air ($\mu g/m^3$), C_{win} - chemical concentration in the inlet water ($\mu g/m^3$), f_w - chemical's weight fraction
721 in the product, G_{ha} - emission rate from headspace to indoor air ($\mu g/s$), K_{aw} - air-water partition coefficient (unitless), M - mass
722 of product used (g), m - chemical mass applied (μg), MW_c - molecular weight of the chemical (g/mol), P_V - saturated vapor
723 pressure of the chemical (Pa), Q_{eahs} - air ventilation rate of the appliance's headspace (m^3/s), R - ideal gas constant (8.314
724 J/mol-K), T - temperature (K), t_{vol90} - the time for 90% of a pure chemical film to volatilize, V_{eaw} - volume of the liquid phase (m^3),

V_{eahs} - headspace volume (m^3), ϕ_{liq_all} - overall liquid-phase mass transfer coefficient (m/s), ϕ_{gas_all} - overall gas-phase mass transfer coefficient (m/s), ϕ_{liq} - liquid-phase mass transfer coefficient (m/s), ϕ_{gas} - gas-phase mass transfer coefficient (m/s).

Key parameters and data availability

The key chemical-specific parameters include the dimensionless Henry's Law constant that is also commonly known as air-water partition coefficient K_{aw} , the overall gas-phase mass transfer coefficient ϕ_{gas_all} and the overall liquid-phase mass transfer coefficient ϕ_{liq_all} . The K_{aw} can be predicted by several publicly available QSAR programs such as HENRYWIN within EPISuite (USEPA, 2012). The overall mass transfer coefficients can be predicted based on the two-film mass transfer theory (Howard-Reed et al., 1999; McCready, 2013) by the liquid-phase mass transfer coefficient ϕ_{liq} and the gas-phase mass transfer coefficient ϕ_{gas} (Eqs. 3.2-8a & 8b), for which estimation methods have been described by Guo and Roache (Guo and Roache, 2003).

Product-specific key parameters include the mass of product (detergent/softener) used (M) and weight fraction of the chemical in the product (detergent/softener) (f_w). Mass of product used can be obtained from studies on the exposure factors of personal and home care products (Isaacs et al., 2014; Park et al., 2015; Sanderson et al., 2006) and the ConsExpo Cleaning Products Fact Sheet (Prud'Homme de Lodder et al., 2006). The chemical's weight fraction can be obtained from the product's formulations, or can be estimated from frame formulations (EC, 2013) or typical compositions of similar products (Prud'Homme de Lodder et al., 2006).

System-specific key parameters include the volumes of headspace (V_{eahs}) and water (V_{eaw}) inside the dishwasher/washing machine and headspace ventilation rate (Q_{eahs}). Howard et al. have measured the volumes and headspace ventilation rates using commercially available residential dishwashers (Howard-Reed et al., 1999) and washing machines (Howard and Corsi, 1998).

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, the EFAST CEM and IAQX models (Eqs. 3.2-1 to 3.2-4) are simple, but they do not account for the characteristics of an enclosed appliance (e.g., limited air exchange with the indoor air) and will lead to over-prediction of the emission to air. The more complex two-phase mass balance model can more accurately represent the enclosed appliance and provide more accurate emission estimations. As above-mentioned for washing machines, the mass balance model considers the fill cycle as a separate and different process from the wash/rinse cycle, so different models should be used for these two types of cycles, as represented by Eqs. 3.2-5 and 3.2-6. The model solution is relatively simple for dishwashers and the wash/rinse cycle of washing machines (Eq. 3.2-5), where explicit analytical solutions are available (Howard-Reed et al., 1999; Howard and Corsi, 1998). We propose that this mass balance model can be further simplified to facilitate HT analysis, using the equilibrium assumption between the liquid and gas phases. As reported in (Howard-Reed et al., 1999) the time needed to reach such equilibrium is often relatively short, which is why it can be assumed that the equilibrium exists for the whole time of operation. Then, the mass balance can be described by Eqs. 3.2-7a to 7c, and a simple analytical solution with the form of a single exponential decay can be obtained. However, due to the assumption of equilibrium, this simplifying assumption will yield slightly over-estimated air emission rates.

3.2.2 Transfer from appliance inner space to object surfaces

Existing models

After washing, residues of laundry detergents or dishwashing liquids may remain on the surface of clothing or dishware which can lead to subsequent dermal or oral exposures. This process is often ignored (Glen et al., 2012; Shin et al., 2015b), or estimated using simplified assumptions as a first proxy (Isaacs et al., 2014; Prud'Homme de Lodder et al., 2006; Sanderson et al., 2006).

For detergent residues on washed fabric (e.g. clothes), a common practice is to assume that a fixed percentage of chemicals within the detergents are deposited on the fabric. For example, ConsExpo assumes 20% of the chemicals in detergents are deposited on the clothing for detergent powder, detergent liquid and fabric conditioners after machine or hand washing, which is a value based on experimental data on residues of linear alkylbenzene sulphonate and fatty acid salts (Prud'Homme de Lodder et al., 2006). However, ConsExpo also acknowledges that the fraction deposited should depend on the type of chemical and on the product itself (Prud'Homme de Lodder et al., 2006). Different from ConsExpo, another study assumes that 1% of laundry detergents and fabric conditioners will be retained on the clothing based on internal data from the Soap and Detergent Association (Isaacs et al., 2014; Sanderson et al., 2006). Corea et al. (Corea et al., 2006) mentioned an empirical model to estimate the deposition of chemicals on washed fabric which calculates the equilibrium partition coefficient between cotton and an aqueous fabric conditioner solution from the octanol-water partition coefficient K_{ow} , but the model details were not presented. Their results using the empirical data (Corea et al., 2006) would lead to 10% - 90% of the fragrance allergens in fabric conditioner deposited on the washed fabric. No other mechanistic models were located in the literature.

For detergent residues on washed dishware, SHEDS-HT (Isaacs et al., 2014) assumes that 1% will be in contact with skin after machine wash and 5% after hand wash, whereas oral exposure through eating and drinking from dishware is not considered. In contrast, for hand wash (i.e. manually washing dishes) ConsExpo assumes that the concentration of chemical in the residual water on undried dishware can be calculated by dividing the amount of chemical applied (e.g., 7g per event) by the total volume of wash water used (e.g., 5 L per event) (Prud'Homme de Lodder et al., 2006). This concentration (g/mL) is multiplied by the fixed amount of water left on dishes (5.5×10^{-5} mL/cm²) to calculate the mass of chemical residues on dishes (g/cm²), which can further be multiplied by the dish area in daily contact with food (e.g. 5400 cm²) to estimate oral exposure via consuming the food that was in contact with the washed dish (Prud'Homme de Lodder et al., 2006). For machine washing, the quantity of chemicals left on dishes and also the oral exposure are simply assumed to be 20% of those for hand wash as calculated above (Lodder et al., 2006b).

Key parameters and Applicability for LCA, CAA and HTS

Suitable models are lacking for the transfers of chemicals from detergent solutions to clothing and dish ware. As a result, no key parameters could be determined. Currently, the common practice is to assume a fixed and usually upper-bound percentage retained regardless of chemical or dish properties, which may be acceptable for conservative approaches, but may not be appropriate for comparative approaches like LCA and CAA which is based on average rather than conservative estimates. Therefore, both empirical and modeling approaches are needed to better understand transfers of chemicals from detergent solutions to clothing and dishware in order to support LCA, CAA and HTS.

3.3 Transfers of chemicals from object surfaces

Chemicals on object surfaces in liquid or semi-liquid phase can be transferred to the indoor and near-person air through volatilization (Section 3.3.1). Examples include surface cleaners and paints that are applied on the surfaces of walls, flooring or furniture as well as spilled liquids. Chemicals present in liquid phase in open tanks, drums or buckets, although uncommon for consumer use in residential settings, can also be transferred to the indoor air through volatilization and will in principle follow the same physical processes as chemicals on object surfaces. Chemicals in solid (particulate) phase can be transferred to indoor air through particle resuspension, which is discussed in Section 3.5.2. Besides the transfers to indoor air, chemicals on object surfaces can also be transferred to skin surface via dermal contact, such as pesticide residues as discussed in Section 3.3.2.

3.3.1 Transfer from object surfaces to indoor and near-person air

Existing models

Several models use simple explicit equations to estimate the volatilization rate without the need to solve a system of mass balance equations. The simplest models are originally designed for occupational exposures, which assume a constant volatilization rate for occupational exposures to pure liquids open to the air with a fixed surface area and temperature (Eqs. 3.3-1 to 3.3-3) (Keil and Nicas, 2003; Keil et al., 2009).

In SHEDS-HT which is specifically for consumer product exposures, the volatilization rate of chemicals from consumer products is assumed to be proportional to the chemical's vapor pressure (Eq. 3.3-4), a refinement of an instantaneous release assumption (Isaacs et al., 2014). It is further assumed that a chemical with a vapor pressure equal to the atmospheric pressure would fully volatilize in one minute given enough air volume to avoid concentration saturation. Although an additional check is performed to guarantee that the calculated air concentration would not exceed the saturation air concentration, this model greatly over-estimates the volatilization rate for most substances since it ignores the effects of liquid volume, surface area and temperature on volatilization (Keating et al., 1997; Keil and Nicas, 2003).

The assumption of a constant volatilization rate may not always hold true, especially when small quantities of solutions are applied to surfaces. As volatilization continues the surface area and volume of the liquid will decrease, both of which would lead to reduced volatilization rate. Keil et al. (Keil and Nicas, 2003) proposed that when a solution or solvent is instantaneously and homogeneously applied to a surface, the volatilization process can be approximated by an exponentially decreasing volatilization rate (Eqs. 3.3-5a & 5b).

EPA's E-FAST CEM model (USEPA, 2007) also employs an exponentially decreasing rate for the volatilization process. This model is more complex than Keil's model as it considers an incremental source scenario where the application area is divided into many segments, and the product is applied to the segments one after another with a constant application rate over the specified duration of use. For each segment, the chemical in the product applied has an exponentially decreasing volatilization rate given by Eq. 3.3-6. Thus, the volatilization rate for the whole application area at a given time is a combination of the volatilization from a newly applied segment and exponentially declining volatilizations from previously applied segments (USEPA, 2007). As an example of a consumer product, the final equations for the volatilization rate from a general purpose cleaner applied to a household indoor surface area are given by Eq. 3.3-7a (USEPA, 2007). For products applied as solutions and then dry and stay on the applied surfaces, such as Latex paint, E-FAST CEM uses a double exponential model

to account for an initial fast release governed by volatilization from the solution and a following slow release controlled by diffusion as the paint dries (Eq. 3.3-8a) (USEPA, 2007). In this model, only 25% of the applied chemical mass within the paint is assumed to be volatilized as the remaining mass fraction becomes trapped in the painted substrate when it dries (USEPA, 2007).

More complex models aim at describing the volatilization process more precisely by using two coupled differential mass balance equations, one for liquids (Eq. 3.3-9a) and the other for indoor air (Eq. 3.3-9b) (Delmaar et al., 2005; Earnest and Corsi, 2013). The second term on the right side of Eq. 3.3-9b describes the increase in mass due to application of the product at a constant rate onto a defined area (such as painting a large wall), which will become zero if the entire product mass is applied simultaneously (Delmaar et al., 2005) as a pulse. For this case, two different methods are available to derive the volatilization rate. ConsExpo uses one that depends on vapor pressure (Eq. 3.3-10a) (Delmaar et al., 2005), while Earnest et al. (Earnest and Corsi, 2013) expressed the rate equation in terms of concentrations (Eq. 3.3-11). The mass balance equations (Eqs. 3.3-9a & 9b) can be solved analytically if the liquid volume is assumed constant. However, if the volume decreases or increases over time, numerical solutions would be necessary.

Table 6. Equations to model the transfer of chemicals on object surfaces to indoor air via volatilization

Constant volatilization rate	
(1) Mackay and Matsugu	
	$G_{vol} = \frac{0.289}{60} \cdot \left(\frac{D_a}{v}\right)^{0.67} \cdot u^{0.78} \cdot L_{vol}^{-0.11} \cdot \frac{P_V}{RT} \cdot MW_c \cdot A_{vol} \quad (3.3-1)$
(2) Gray	
	$G_{vol} = \frac{1300}{60} \cdot D_a^{1.9} \cdot v^{-0.9} \cdot \left(\frac{100vu}{D_a}\right)^{0.625} \left(\frac{v}{D_a}\right)^{0.3} \cdot L_{vol}^{-0.11} \cdot \sqrt{\frac{P_{atm}}{P_{atm}-P_V}} \cdot \frac{P_V}{RT} \cdot MW_c \cdot A_{vol} \quad (3.3-2)$
(3) Hummel et al.	
	$G_{vol} = \frac{1}{60} \cdot (0.166 \cdot MW_c^{0.833} \cdot P_V \cdot \left(\frac{1}{MW_c} + \frac{1}{29}\right)^{0.25} \cdot A_{vol}) / T^{0.05} \cdot \sqrt{\frac{u}{L_{vol} \cdot P_{atm}}} \quad (3.3-3)$
SHEDS-HT model	
	$G_{vol} = M \cdot f_w \cdot \frac{10^6}{60} \cdot \frac{P_V}{P_{atm}}, \quad m_{vol} = G_{vol} \cdot t_{app}, \quad C_g = \frac{m_{vol}}{V} \cdot 10^6 \quad (3.3-4)$
Keil's model: exponentially decreasing volatilization rate	
	$G_{vol}(t) = \delta \cdot m_{liq} \cdot e^{-\delta t} \quad (3.3-5a)$
	$\delta = \frac{1}{60} \cdot (0.000524 \cdot P_V + 0.0108 \cdot \frac{A_{vol}}{V_{liq}}) \quad (3.3-5b)$
E-FAST CEM model	
(1) Exponentially decreasing volatilization rate for a single source segment	
	$G_{vol}(t) = G_{vol}(0) \cdot e^{-k_{vol}t} \quad (3.3-6)$
(2) Volatilization rate for a general purpose cleaner	

$$G_{vol}(t) = \frac{m_{90\%}}{t_{app}} [(1 - e^{-k_{vol}t}) - (1 - e^{-k_{vol}(t-t_{app})}) \cdot W] \quad (3.3-7a)$$

$$W = \begin{cases} 0, & t < t_{app} \\ 1, & t > t_{app} \end{cases} \quad (3.3-7b)$$

$$k_{vol} = \frac{\ln(10)}{t_{vol90}}, \quad t_{vol90} = \frac{145}{(MW_c \cdot P_v)^{0.9546}} \cdot 3600 \quad (3.3-7c)$$

(3) Volatilization rate for Latex paint

$$G_{vol}(t) = \frac{m_{25\%}}{t_{app}} ([0.1 \cdot (1 - e^{-k_{vol1}t}) + 0.9 \cdot (1 - e^{-k_{vol2}t})] - [0.1 \cdot (1 - e^{-k_{vol1}(t-t_{app})}) + 0.9 \cdot (1 - e^{-k_{vol2}(t-t_{app})}) - 1] \cdot W) \quad (3.3-8a)$$

$$k_{vol1} = \frac{233.25 \cdot P_v}{24 \cdot 3600}, \quad k_{vol2} = \frac{0.0000584 \cdot MW_c}{24 \cdot 3600} \quad (3.3-8b)$$

Mass balance model

$$V \frac{dC_g}{dt} = G_{vol} - Q \cdot V \cdot C_g \quad (3.3-9a)$$

$$V_{liq} \frac{dC_{liq}}{dt} = -G_{vol} + M/t_{app} \cdot f_w \quad (3.3-9b)$$

(1) ConsExpo method for deriving G_{vol} :

$$G_{vol} = \phi_{vol} \cdot (P_{eq} - P_{air}) \quad (3.3-10a)$$

$$P_{eq} = \frac{P_v \cdot C_{pro,c}}{C_{pro,c} + C_{pro,r} \cdot \frac{MW_c}{MW_r}} \quad (3.3-10b)$$

(2) Earnest's method for deriving G_{vol} :

$$G_{vol} = \phi_{gas_all} \cdot A_{vol} \cdot (K_{aw} \cdot C_{liq} - C_g) \quad (3.3-11)$$

869 A_{vol} - surface area of liquid pool from which a chemical volatilizes (m^2), C_g - gas-phase chemical concentration in room air
870 ($\mu g/m^3$), $C_{pro,c}$ - concentration of chemical in the product ($\mu g/m^3$), $C_{pro,r}$ - concentration of the rest of the material in the product
871 ($\mu g/m^3$), D_a - diffusion coefficient in air (m^2/s), f_w - mass fraction of chemical in the product, G_{vol} - volatilization rate ($\mu g/s$), G_{vol}
872 (0) - initial volatilization rate at time 0 ($\mu g/s$), K_{aw} - air-water partition coefficient, k_{vol} - first-order volatilization rate constant (s^{-1})
873 k_{vol1} - rate constant for the first exponential (s^{-1}), k_{vol2} - rate constant for the second exponential (s^{-1}), L_{vol} - surface length of
874 liquid pool (m), M - mass of product applied (g), m_{liq} - mass of liquid (solution or solvent) (μg), m_{vol} - total chemical mass that is
875 volatilized into air (μg), $m_{90\%}$ - 90% of the chemical mass applied (μg), $m_{25\%}$ - 25% of the chemical mass applied (μg), MW_c -
876 molecular weight of the chemical (g/mol), MW_r - average molecular weight of the rest of the material in the product, P_v -
877 chemical's saturation vapor pressure (Pa), P_{atm} - atmospheric pressure (Pa), P_{eq} - equilibrium vapor pressure of a chemical in a
878 mixture (Pa), P_{air} - chemical's actual vapor pressure (Pa), R - ideal gas constant (8.3144 J/mol/K), T - temperature (K), t_{app} -
879 duration of product use/application (s), t - time (s), u - air speed (m/s), V - room volume (m^3), ν - kinematic viscosity of air (m^2/s),
880 δ - volatilization rate parameter (s^{-1}), ϕ_{vol} - mass transfer coefficient of volatilization process (m/s), ϕ_{gas_all} - overall gas-phase
881 mass transfer coefficient (m/s).

882

883 Key parameters and data availability

884 For the simpler models represented by Eqs. 3.3-1 to 3.3-4, the key parameters are mostly chemical-
885 specific, including molecular weight (MW), vapor pressure (P_v) and diffusion coefficient in air (D_a). While
886 MW and vapor pressure can be easily obtained, diffusion coefficients in air usually must be estimated
887 for example by mathematical relationships from the chemical's molecular weight/molar volume and
888 temperature (Huang and Haghighat, 2002; Keil et al., 2009).

For the more complex models represented by Eqs. 3.3-9 to 3.3-11, the key parameter is also chemical-specific, which is either the mass transfer coefficient ϕ_{vol} if equation (3.3-10a) is used as the source term, or the overall gas-phase mass transfer coefficient ϕ_{gas_all} if equation (3.3-11) is used. ConsExpo provides two methods, Langmuir's method and Thibodeaux's method, to estimate ϕ_{vol} from the chemical's molecular weight and the surface area of liquid (Delmaar et al., 2005). The method for estimating ϕ_{gas_all} is described in Section 3.2.1.

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, the constant volatilization rate models (Eqs. 3.3-1 to 4) are simple, but they would lead to large over-prediction of the volatilization rate for most consumer use scenarios. The models with exponential decrease (Eqs. 3.3-5 to 8) are also simple and they can capture the decreasing volatilization rate, and hence are generally more accurate than the constant rate models. Eqs. 3.3-5 & 3.3-6 are applicable to the situation that the entire product is applied simultaneously to the whole surface area. For the situation that the product is applied at a constant rate to cover a defined surface area, such as surface cleaning and painting, equations (3.3-7 & 8) are more appropriate. However, in Eqs. 3.3-7 & 3.3-8 it is assumed in advance that 90% of the chemicals in a general purpose cleaner and 25% of those in Latex paint will be volatilized, which is likely not true over a range of chemicals and within other product types, since the physiochemical properties of other chemical-product combinations are different which will affect the mass volatilized. Generally, the mass balance models (Eqs. 3.3-9 to 11) are more appropriate to cover a wide range of chemical-product combinations, but numerical solutions are generally needed unless the liquid volume is assumed constant, meaning the bulk solvent is assumed not to volatilize. Thus, the mass balance models with the assumption of constant volume can be consider as a first approximation, and future model developments may focus on simpler models (i.e. no need of numerical solutions) which can well account for the decreasing volume and the incremental source. It should also be noted that surface degradation is not considered in any of the existing models, which appears to be a conservative assumption appropriate for risk assessments. Thus, to make the models more suitable for LCA and CAA where "average situations" are considered, surface degradation needs to be included as a loss process in the mass balance models.

3.3.2 Transfer from object surfaces to skin surface

Existing models

In the near-field environment, the surface of an object can be contaminated by various chemicals through intentional application, abrasion from within the object, and dust deposition from indoor air. Contact with this object surface, such as hand contact or crawling, will result in the transfer of a fraction of the chemicals on object surfaces to the human skin surface.

A simple way to estimate the transfer from object surface to skin surface is to multiply the chemical mass per area on object surface ($\mu\text{g}/\text{m}^2$) by the dermal transfer coefficient (m^2/s) and contact duration (s) (Eq. 3.3-12a). This method has been employed by SHEDS-MM (Glen et al., 2012). Its later HT version, SHEDS-HT (Isaacs et al., 2014), further assumes that only a fraction of the chemical present on surfaces – represented by an additional parameter f_{avail} – can be removed by touching (Eq. 3.3-12b). This simple method has also been employed by ConsExpo for the dermal rubbing off mode (Delmaar et al., 2005) and by Liao et al. (Liao and Kannan, 2011) to estimate the daily exposure of bisphenol A (BPA) from the handling of paper currencies.

While the above method evaluates the exposure by the duration of contact, a second method evaluates it by the frequency of contact using the microactivity approach (Shin et al., 2012; Zhang et al., 2014) (Eq. 3.3-13). This approach assumes that the chemical transfer is the same for each event of contact, which might not be reasonable since the contact duration of each event may differ, which will affect the transfer efficiency.

Table 7. Equations to model the transfer of chemicals on object surfaces to skin surface

Transfer coefficient approach:	
(1) SHEDS-MM format	
	$m_{os_ss} = SC_{obj} \times TC_{os_ss} \times t_{derm} \quad (3.3-12a)$
(2) SHEDS-HT format	
	$m_{os_ss} = SC_{obj} \times TC_{os_ss} \times f_{avail} \times t_{derm} \quad (3.3-12b)$
Microactivity approach: ExpoDat	
	$m_{os_ss,i} = SC_{obj,i} \cdot A_{os} \cdot FQ_{os,i} \cdot TE_{os_ss,i} \quad (3.3-13)$

A_{os} - surface area of the skin contacted (m^2 /event), f_{avail} - fraction of the chemical present on object surface that can be removed by touching (unitless), m_{os_ss} - chemical mass that is transferred from object surface to the skin surface (μg), $m_{os_ss,i}$ - chemical mass that is transferred from object surface i to the skin surface (μg), $N_{os,i}$ - number of object-to-skin contacts for surface i (unitless), SC_{obj} - chemical mass per area on object surface ($\mu g/m^2$), $SC_{obj,i}$ - chemical mass per area on object surface i ($\mu g/m^2$), TC_{os_ss} - transfer coefficient from object surface to skin surface (m^2/s), $TE_{os_ss,i}$ - transfer efficiency of the chemical from surface i to skin surface (unitless), t_{derm} - dermal contact duration (s).

Key parameters and data availability

Chemical-specific parameters include the dermal transfer coefficient TC_{os_ss} for the transfer coefficient approach (Eq. 3.3-12) and the transfer efficiency $TE_{os_ss,i}$ for the microactivity approach (Eq. 3.3-13). TC_{os_ss} is typically derived experimentally by measuring the mass collected on a cotton dosimeter (e.g., gloves, bodysuit) worn by an individual contacting an chemical for a known time ($\mu g/s$) and dividing that by an average chemical mass per object surface area ($\mu g/cm^2$) (Glen et al., 2012). This, however, would limit its application since it is costly and time-consuming to obtain experimental data for every chemical. Dermal transfer efficiency ($TE_{os_ss,i}$) represents the fraction of chemical on a contacted surface that is transferred onto the skin. $TE_{os_ss,i}$ is also generally measured (Cohen Hubal et al., 2007; Lu and Fenske, 1999). However, for simplicity, Shin et al. applied default values for this parameter to different surfaces: 3.35% for transfer efficiency from carpet to hand and 3.15% for transfer efficiency from vinyl floor to hand (Shin et al., 2012). This approach assumes the same transfer efficiency for different chemicals from the same type of surface, which may be problematic when comparing substances with widely different chemical properties.

The chemical mass per area on object surface (SC_{obj}) is both chemical- and product-specific and is required for both models. It is influenced by three identified mechanisms: application on the object, abrasion from within the object, or deposition on the object (e.g. due to dust). The chemical mass per area on object surface can be measured experimentally using surface wipe samples (Stapleton et al., 2008; Watkins et al., 2011) or predicted/calculated using mathematical models. When chemicals are applied to object surfaces via solutions (e.g. cleaning fluids), then the chemical mass per area on object

surface can be calculated by dividing the chemical mass applied (can be calculated by multiplying the amount of solution applied by the concentration in solution) by the object surface area, for which the loss by volatilization (Section 3.3.1) may also be considered. Chemical releases to the object surface from within the object via abrasion have been discussed in Section 3.1.4. When chemicals are transferred to the object surface via dust deposition from air, the chemical mass per area on object surface can be calculated by multiplying the concentration in dust by the dust amount per area on the object surface.

The key system-specific parameter is the contact frequency $FQ_{os,i}$ for the microactivity approach. The frequency of contacts for carpet, vinyl floor and objects can be obtained from various studies on children's microactivities (AuYeung et al., 2006; Freeman et al., 2000; Freeman et al., 2005; Reed et al., 1999; Zartarian et al., 1996), and Shin et al. (Shin et al., 2012) gave the average values of 11, 12 and 115 events/day.

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, both the transfer coefficient and microactivity approaches are easy to use since they are based on simple multiplications. However, a substantial limitation of both methods is the difficulty to explicitly estimate the transfer coefficient or transfer efficiency as a function of chemical properties. Thus, it is difficult to apply these models to chemicals with no experimental data of transfer coefficients or efficiencies. Although some default values might be used for these parameters, this would lead to inaccurate estimates. Therefore, new chemical property-based relationships reflecting the underlying mechanisms need to be developed to predict the transfer-related parameters to better support the HT use of these models (i.e., application to a wide range of chemical-product combinations).

3.4 Transfers of chemicals from skin surface

Chemicals deposited or applied on skin surface can penetrate through the stratum corneum and be absorbed by the epidermis, which is addressed in Section 4.3 as transfer to a human body compartment (epidermis). Chemicals on skin surface may also volatilize to the indoor and near-person air (Section 3.4.1), which may contribute to inhalation exposure and dermal uptake of gaseous chemicals (Dudzina et al., 2015; Tibaldi et al., 2014).

3.4.1 Transfer from skin surface to air

Existing models

The transfer of chemicals in liquid or semi-liquid phase from skin surface to air is a similar process as the volatilization of chemicals from object surface (Section 3.3.1), except that the temperature and convective mass transfer rate on skin surface are generally higher than those on object surfaces. The IH SkinPerm (Tibaldi et al., 2014) and the REACH guidance for occupational exposure assessment (ECHA, 2012) have employed a simple method to calculate the volatilization rate from a liquid film on the skin (Eq. 3.4-1). In this method it is assumed that the volatilization rate from the skin is constant, which is analogous to the constant volatilization rate methods for volatilization from object surfaces (Eqs. 3.3-1 to 3.3-3). However, as mentioned in Section 3.3.1, the assumption of constant volatilization rate may not hold, especially considering the relatively small mass of chemicals applied on skin surface via e.g. skin care products and skin absorption as process competing with volatilization.

Thus, a more accurate approach is to solve a chemical mass balance to determine the time-dependent volatilization rate. Ernstoff et al. (Ernstoff et al., 2016) presented a mass balance model for chemicals on skin surface, which included volatilization and skin absorption as two competing processes (Eqs 3.4-2a to 2c), and the fractional mass volatilized at time t is given by Eq. 3.4-3. This model is also able to calculate the fraction of chemical that is finally washed off from skin and then transferred to wastewater treatment plant (WWTP), which is an important transfer process connecting the near-field and far-field environments (Ernstoff et al., 2016).

Table 8. Equations to model the transfer of chemicals from skin surface to air

REACH model	
$G_{vol} = \frac{0.0111 \cdot u^{0.96} \cdot \left(\frac{0.06}{3600} \sqrt{\frac{76}{MW_c}}\right)^{0.19}}{v^{0.15} \cdot L_{vol}^{0.04}} \cdot 10^6 \cdot \frac{P_v}{RT} \cdot MW_c \cdot A_{vol} \quad (3.4-1)$	
Ernstoff et al.'s mass balance model	
(1) Mass balance equations:	
$\frac{dm_p}{dt} = -m_p(k_{ps} + k_{pa})$	(3.4-2a)
$\frac{dm_s}{dt} = k_{ps}m_p$	(3.4-2b)
$\frac{dm_a}{dt} = k_{pa}m_p$	(3.4-2c)
(2) Solution for the fractional mass volatilized at time t :	
$f_{vol} = \frac{k_{pa}}{k_{ps} + k_{pa}} (1 - e^{-(k_{ps} + k_{pa})t})$	(3.4-3)

A_{vol} - surface area from which a chemical volatilizes (m^2), f_{vol} - fraction of mass volatilized from skin surface to air, G_{vol} - volatilization rate from skin surface to air ($\mu g/s$), k_{ps} - a rate constant for transfer from the product on skin surface into the skin (s^{-1}), k_{pa} - a rate constant for transfer from the product on skin surface into the air (s^{-1}), L_{vol} - surface length of liquid from which a chemical volatilizes (m), MW_c - chemical's molecular weight (g/mol), m_p - chemical mass in the product that is applied to skin surface (μg), m_s - chemical mass in skin (μg), m_a - chemical mass in air (μg), P_v - chemical's vapor pressure (Pa), R - ideal gas constant (J/mol/K), T - temperature (K), u - air speed (m/s), v - kinematic viscosity of air (m^2/s), 10^6 - conversion factor from g to μg .

Key parameters and data availability

For the simple constant rate model (Eq. 3.4-1), key parameters include the chemical's molecular weight and vapor pressure that are chemical-specific, room air temperature, air speed over skin surface and surface length of volatilization that are system-specific, of which the first three parameters can be easily obtained from existing databases. For the air speed over skin surface and the surface length of volatilization, Tibaldi et al. (Tibaldi et al., 2014) give default values of 0.3 m/s and 0.1 m, respectively, which can be adjusted according to the real situation being evaluated.

For the mass balance approach (Eqs. 3.4-2 to 3.4-4), the key parameters are the two rate constants k_{ps} and k_{pa} which are both chemical- and product-specific. Both parameters are dependent on the thickness

of the product on the skin, which may be estimated by the volume of product applied and skin surface area covered. Parameter k_{ps} is also a function of the skin permeation coefficient, which is discussed in Section 4.3, while k_{pa} is a function of the air-water partition coefficient K_{aw} , which is available for many chemicals and can be predicted by QSAR programs such as HENRYWIN within EPI Suite (USEPA, 2012). The equations for calculating k_{ps} and k_{pa} can be found in the supporting info of Csiszar et al. (Csiszar et al., 2016).

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, both models reviewed are simple in their mathematical format. However, the constant volatilization rate model (Eq. 3.4-1) may lead to over-prediction of the chemical mass volatilized to air due to the assumption of constant rates. In contrast, the mass balance model (Eqs. 3.4-2 to 3.4-4) would provide a more accurate prediction of the volatilized mass and mass transferred to WWTP since it considers the competing effect of dermal absorption, which would be more suitable for LCA, CAA and HT analysis.

3.5 Transfers of chemicals from indoor and near-person air

The indoor air connects the various compartments in the near-field environment. Chemicals can be transferred to indoor air from different compartments, as detailed in previous sections. Chemicals can also be directly released to the indoor air (i.e., the indoor air is the compartment of entry), such as air sprays (Section 3.5.1). Once in the air, the chemicals may go through various transport and transformation processes, such as removal by air ventilation, sorption to object surfaces, sorption to airborne particles and subsequent particle deposition, gas-phase degradation, as well as interaction with human occupants. These processes are typically considered simultaneously in compartmental indoor transport and fate models, which have been studied extensively and will only be summarized in Section 3.5.2.

3.5.1 Transfer of chemicals in sprays

Existing models

Spray products, such as air fresheners, hair sprays, and insect repellents, can be considered as intentional, direct releases to indoor and near-person air. Chemicals which volatilize (into gas phase) through spraying are typically assumed to be 100% released into indoor air. However, most spray products generate liquid-phase aerosols, or colloids of fine droplets. Smaller droplets tend to remain in the air while larger droplets will deposit on the floor or other surfaces, and are thus removed from the indoor air compartment (Delmaar et al., 2005). Therefore, chemicals in sprays finally would have a certain fraction transferred to air while the remaining fraction transferred to indoor surfaces. Typically, propellant gas sprays (air fresheners, hair sprays, fly sprays) produce smaller droplets, while pump sprays (paints) emit larger droplets, although both product classes contain a distribution of droplet sizes (Delmaar et al., 2005; Rothe et al., 2011). A simple way to account for aerosol suspension is to introduce a fixed airborne fraction which indicates the fraction of chemicals released from the spray that will be suspended in air (Delmaar et al., 2005; Isaacs et al., 2014). Dynamic mass balance models can also be used to simulate the deposition and (re)suspension of the full size distribution of aerosols generated by the spray, and to determine the airborne chemical mass at a certain time. An example of such a model has been presented in ConsExpo (Delmaar et al., 2005). This model establishes and solves an equation system for each diameter value of the aerosols, and then integrates over the entire particle distribution to obtain the total chemical mass released to air (Delmaar et al., 2005). Another area of research is

consumer sprays containing engineered nanoparticles, for which the size distribution of the nanosized aerosols generated has been investigated and an inhalation exposure model has been proposed by Lorenz et al (Lorenz et al., 2011).

Another important aspect for sprays is the volume of the indoor air into which the droplets disperse, which determines the chemical concentrations in air. To account for this, some models use the room volume (Delmaar et al., 2005). However, spray products are often applied near or onto a person and the near-person air concentration is thus expected to be higher than the concentration in the bulk air within the rest of the room. Assuming a uniform concentration in the room could underestimate exposure via inhalation. To avoid this issue, some models define a cloud volume containing the majority of sprayed aerosols. ConsExpo suggests a default value of 0.0625 m³ for cloud volume, which matches a cone measuring 1 m in length and 0.5 m in diameter (Delmaar et al., 2005). Likewise, SHEDS-HT assumes a uniform distribution (0.0425 - 0.0825 m³) having a mean equal to 0.0625 m³ for the cloud volume, and remaining constant throughout the considered exposure time (Isaacs et al., 2014). It should be noted that SHEDS-HT heavily relies on ConsExpo and often simply generates a distribution around a nominal ConsExpo value for several parameters. In reality, the cloud volume will gradually increase until it reaches the room volume, but complex models would be needed to simulate the complex underlying dispersion processes (Delmaar et al., 2005). A reasonable approximation to account for the change of the cloud size with time is to use a two-zone model, which divides the room into an inner (near-person) zone and an outer (rest of the room) zone. In this way, the dispersion of the cloud can be approximated by the air exchange between the inner and outer zones. The two-zone model is further discussed in Section 3.5.2.

Key parameters and data availability

The key parameters required to estimate the transfer of chemicals from sprays are primarily product-specific, that is, dependent on the properties of the spray product. For the fixed airborne fraction method, the data needed include the type of spray and the corresponding airborne fraction value. ConsExpo factsheets provide default values of airborne fractions for various types of sprays, including cosmetics sprays, cleaning product sprays, agricultural sprays and spray paints (Bremmer et al., 2006a; Bremmer and Engelen, 2007; Bremmer et al., 2006b; Lodder et al., 2006a). For the mass balance model, key parameters include the initial size distribution and the density of the particles generated by the spray. ConsExpo factsheets also provide default values of particle size distribution and density for various sprays (Bremmer et al., 2006a; Bremmer and Engelen, 2007; Bremmer et al., 2006b; Lodder et al., 2006a). Several other studies have measured the detailed particle size distributions for specific consumer sprays such as hair sprays, anti-odor sprays and surface disinfectant sprays (Hagendorfer et al., 2010; Hussein et al., 2006; Lorenz et al., 2011; Quadros and Marr, 2011).

Applicability for LCA, CAA and HTS

In terms of suitability for LCA, CAA and HTS, the fixed airborne fraction is simple and straightforward, but it can only give rough estimates for a certain kind of spray, that is, it cannot account for the actual particle properties of a specific spray product. In contrast, the mass balance model can give more accurate estimates, but it requires the detailed particle properties of the studied spray products which may not be readily available, and it is computationally more complex as it requires the solution of differential equations.

3.5.2 Indoor transport and fate processes

Existing models

There are two common mass-balance approaches for multimedia transport and fate modeling: the traditional mass/concentration-based approach and the fugacity-based approach. The concept of fugacity describes an “escaping” tendency of a chemical from a compartment, which can serve as an equilibrium criterion of chemical partitioning, i.e., if a chemical partitions between two phases or media, it seeks to establish an equal fugacity in both phases or media (Mackay, 2010). Several fugacity models have been applied to simulate indoor transport and fate (Bennett and Furtaw, 2004; Matoba et al., 1998; Shin et al., 2012; Shin et al., 2013; Zhang et al., 2014; Zhang et al., 2009). Matoba et al. (Matoba et al., 1998) modeled the indoor behavior of pesticides sprayed as aerosol droplets into a one-room house divided into seven interconnected compartments: suspended aerosol droplets (large, medium and small), gas-phase air and room materials (floor, wall and ceiling). Considered removal processes include air ventilation, adherence to room materials and subsequent diffusion inside the materials, and degradation by photolysis or oxidation in each compartment (Matoba et al., 1998). Bennett and Furtaw (Bennett and Furtaw, 2004) developed a more detailed two-zone fugacity model which consists of the zone in which the pesticide treatment occurs and an adjoining zone. Both zones have an air compartment and several other compartments representing the surfaces of carpet, vinyl flooring, walls and ceiling; dust particles with a size distribution were included as a phase in the air, carpet and vinyl flooring compartments (Bennett and Furtaw, 2004). In contrast to Matoba’s model where pesticides are modeled as being sprayed into air, in Bennett’s model it is assumed that the pesticides are directly applied to an indoor surface compartment (e.g. carpet) (Bennett and Furtaw, 2004). Advective (ventilation, dust deposition and resuspension) and diffusive transfers were included between air and surface compartments, and degradation due to reaction with OH radicals was considered only for the air compartment (Bennett and Furtaw, 2004). Bennett’s model has been employed by several later studies (Isaacs et al., 2014; Shin et al., 2015b; Shin et al., 2012; Shin et al., 2013; Zhang et al., 2014; Zhang et al., 2009). For example, Zhang et al. (Zhang et al., 2009) adapted the model to simulate the emissions and fate of PBDEs indoors, and added a compartment of polyurethane foam (PUF) furniture, which has PBDEs added up to 10% and can act as a source or sink for PBDEs depending on emissions and fugacities of other compartments. Zhang’s model considered the dust particles as a separate phase in each of the modeled compartments (Zhang et al., 2009). In a later PBDE study, Zhang et al. (Zhang et al., 2014) considered the orientation of indoor surfaces and included human feedback on the chemical mass balance (e.g., chemical loss by human intake and chemical gain by human respiration). Shin et al. (Shin et al., 2013) used Bennett’s model to estimate the indoor residence times of SVOCs. Within SHEDS-HT, Isaacs et al. (Isaacs et al., 2014) simplified Bennett’s model to two compartments (air and generic surfaces) with each compartment containing two particle phases (nominal large and small particles), and the number of model input parameters was reduced to retain only the most influential parameters, such as octanol-water partition coefficient, vapor pressure, water solubility and degradation rate on surfaces, according to results of a sensitivity study.

The traditional concentration-based mass balance modeling is another commonly used approach to simulate the indoor transport and fate of chemicals. A review by Weschler and Nazaroff (Weschler and Nazaroff, 2008) summarized the various processes (e.g., sorption to indoor surfaces and airborne particles, diffusion into porous substrates and degradation) of SVOCs in indoor environments and the mathematical methods to model these processes. In two later inhalation exposure studies, Wenger et al. (Wenger et al., 2012) and Rosenbaum et al. (Rosenbaum et al., 2015) accounted for various removal

processes including air ventilation, gas-phase degradation, sorption on indoor surfaces, and surface degradation.

When modeling indoor transport and fate processes, three important aspects require special attention: particles, mixing of indoor air, and the role of human occupants. Particles in the indoor environment are crucial to be considered in indoor transport and fate models, since many chemicals, especially SVOCs, may sorb to particles which will alter their transport and fate. Particles may be present on various indoor surfaces or be suspended in indoor air. Sources of indoor particles include ventilation from outdoor air, track-in of outdoor soil (Shin et al., 2013), combustion processes such as cooking and smoking, cleaning activities (Nazaroff, 2004), abrasion of room materials (Liagkouridis et al., 2014) and formation of secondary organic aerosols from reactions between ozone and VOCs emitted indoors (Hodas et al., 2015), while removal processes include ventilation to outdoor air and vacuum cleaning (Shin et al., 2013). Indoor particles can go through various dynamic processes, such as deposition, resuspension, coagulation, and phase change, which have been reviewed by Nazaroff (Nazaroff, 2004). Nazaroff and Cass also proposed a general mathematical model for indoor particle dynamics (Nazaroff and Cass, 1989). More recent studies have used complex computational fluid dynamic (CFD) models to simulate the particle transport and distribution in indoor environments (Chen et al., 2006; Zhang and Chen, 2006). In indoor transport and fate models of chemicals, particles are generally treated as a phase in each relevant compartment, where particle concentrations, emission rates and removal rates are input parameters to the model (Bennett and Furtaw, 2004; Isaacs et al., 2014; Zhang et al., 2009). In contrast, two recent studies have developed a mass balance model for indoor particles, where particles were treated as a “chemical” in relevant compartments, and the mass concentrations, emission and removal rates of particles were predicted by the model (Shin et al., 2013; Zhang et al., 2014).

The imperfect mixing of the indoor air also influences indoor fate and subsequent exposure, however is mostly overlooked or disregarded in most models which consider the indoor air as one well-mixed compartment (Bennett and Furtaw, 2004; Isaacs et al., 2014; Shin et al., 2015b; Shin et al., 2012; Shin et al., 2013; Zhang et al., 2014; Zhang et al., 2009). In the cases of painting or cleaning, or application of personal care products, substantial gradients in chemical concentrations can exist within the air near the human body (Earnest and Corsi, 2013; Keil and Nicas, 2003). First developed by Nicas (Nicas, 1996) and Furtaw et al. (Furtaw et al., 1996), two-zone models, which treat the air space immediately surrounding the human body (inner zone) as a distinct compartment from the bulk room air (outer zone), are a modeling strategy used to address the effects of inhomogeneous air mixing. Two-zone models have been widely used for occupational exposure (Keil et al., 2009; Sahmel et al., 2009), but are a recent development for modeling consumer exposures (Earnest and Corsi, 2013).

Another important aspect of indoor air models is the role of human occupants, since human occupants can affect indoor transport and fate of chemicals through respiration, dermal absorption and physical movements. Most existing indoor models do not consider the potential effects of room occupants on the transport and fate of chemicals. Two recent studies (Little et al., 2012; Weschler and Nazaroff, 2012) suggested that the chemical intake by humans can comprise a significant portion of chemical emissions indoors. Accordingly, a recent indoor model developed by Zhang et al. incorporated human as a three-compartment module into the model system to account for the chemical loss due to human intake (inhalation, ingestion and dermal absorption) and the chemical re-entry due to respiration and dermal permeation (Zhang et al., 2014). Their results indicated that including a human in the indoor mass balance lowers both the concentrations and residence times by up to 100% for chemicals with low volatility (Zhang et al., 2014). The presence of humans within a room can affect some characteristics of the indoor compartment, e.g., the skin surface lipids of human can react rapidly with ozone and

substantially reduce indoor ozone concentrations, which can influence chemical fate for example by enhancing chemical reactions producing byproducts (Weschler, 2015).

Key parameters and data availability

An indoor air transport and fate model may require a large amount (typically > 20) of input parameters. Sensitivity analyses within previous studies suggested that the air ventilation rate is often the most important parameter, and to a lesser extent degradation rates in air and on surfaces, boundary layer thickness over surfaces, water solubility, molecular weight, vapor pressure, Henry's law constant, $\log K_{ow}$, partition coefficients between compartments (Bennett and Furtaw, 2004; Isaacs et al., 2014; Weschler and Nazaroff, 2008; Zhang et al., 2014) and number of occupants (Hodas et al., 2015). While most of these parameters are chemical-specific, the air ventilation rate, boundary layer thickness and number of occupants are system-specific. Most parameters can be easily obtained from the literature or be predicted by QSAR programs, but determining degradation rates and partition coefficients is challenging. Many studies have estimated gas-phase degradation rates assuming only reaction with OH radicals at typical indoor concentrations (Bennett and Furtaw, 2004; Zhang et al., 2014). Wenger et al. extend the gas-phase degradation rate by also considering reaction with ozone and nitrate radicals, which is more comprehensive and is consistent with outdoor modeling (Wenger et al., 2012). SHEDS-HT uses the EPISuite-estimated degradation rate in outdoor air as a simplified proxy (Isaacs et al., 2014). Degradation rates on indoor surfaces are also considered to various extents. Bennett et al. exclude degradation on surfaces due to lacking data and methodologies, which may underestimate the removal rate of chemicals and may overestimate the human exposures (Bennett and Furtaw, 2004). Zhang et al. assume that the surface degradation rates are equal to the gas-phase degradation rate (Zhang et al., 2014), while Wenger et al. assume a generic surface degradation rate for all indoor surfaces approximated by a fixed fraction of 10% of the gas-phase degradation rate (Wenger et al., 2012). Alternatively, SHEDS-HT assume that the indoor surface degradation rates are equal to the mean of the rates in soil and sediment as predicted by EPISuite (Isaacs et al., 2014).

To estimate partition coefficients between compartments such as indoor surfaces and air, previous studies applied empirical correlations based on chemical vapor pressure (Bennett and Furtaw, 2004; Guo, 2002; Isaacs et al., 2014; Wenger et al., 2012; Weschler and Nazaroff, 2008). A more recent study by Holmgren et al. (Holmgren et al., 2012) presents a set of empirical relationships to estimate the material-air partition coefficient using Abraham solvation parameters. A common problem of empirical relationships is their availability across types of materials/surfaces or chemical classes. For example, if a new type of material/surface or a new chemical class is to be evaluated, a new correlation may need to be established using experimental data.

Applicability for LCA, CAA and HTS

The indoor models are able to account for various transport and fate processes. However, a model's complexity depends on the processes considered and the assumptions made. For example, a two-zone model will be more complex than a model considering the same processes but assuming a well-mixed one zone air compartment. For typical indoor models, a set of coupled differential equations needs to be solved to obtain time-varying chemical concentrations or masses, which generally needs numerical solutions (Bennett and Furtaw, 2004; Matoba et al., 1998). Explicit analytical solutions are only available for steady-state calculations (Wenger et al., 2012; Zhang et al., 2014) or greatly simplified models with very few compartments (Isaacs et al., 2014). On the other hand, parameter availability is a major obstacle to estimating indoor fate and transport. As mentioned above, methods are needed to predict the degradation rates and partition coefficients for various indoor surfaces. Therefore, future

development of indoor models for LCA, CAA and HTS purposes, such as simplification of existing models or prediction of key parameters, is necessary. SHEDS-HT presents an encouraging example of adapting the indoor model for HTS, where they reduced the indoor model to two compartments and retained only the most important input parameters, so simplified solutions can be obtained (Isaacs et al., 2014). USEtox 2.0 also provides a simplified approach to include indoor transport and fate processes for LCA (Rosenbaum et al., 2015). Both the SHEDS-HT and USEtox 2.0 approaches can serve as starting point for addressing exposure in CAA, and future research may follow similar strategy to achieve a balance between accuracy and simplicity under the consideration of the specific CAA assumptions.

4. Model review for human exposure processes

4.1 Transfer to respiratory tract

Existing models

Inhalation is the main contributing process to transfer to the respiratory tract from indoor or near-person air (Figure 1). Transfers to the respiratory tract can be approximated by the product of the chemical concentration in air, the inhalation (breathing) rate, and the exposure duration (Delmaar et al., 2005; Glen et al., 2012; Isaacs et al., 2014; Little et al., 2012; Shin et al., 2015b; Shin et al., 2012; Wenger et al., 2012; Zhang et al., 2014):

$$m_{inh} = C_{air} \cdot IR_{inh} \cdot t_{inh} \quad (4.1-1)$$

where m_{inh} is the chemical mass that is transferred to the respiratory tract via inhalation (μg), C_{air} is the bulk gas-phase and particle-phase chemical concentration in air ($\mu\text{g}/\text{m}^3$), IR_{inh} is the average constant inhalation rate (m^3/d), and t_{inh} is the inhalation exposure duration (d).

Equation (4.1-1) calculates the mass of chemical taken in via inhalation, which can be considered as the inhalation-related exposure. Based on this, it may be useful to further identify the fraction of chemical that finally reaches the lungs. Inhaled chemicals may deposit along the respiratory tract and may result in a fraction reaching the lungs, f_{dep} . The mass deposited into the lungs as determined by f_{dep} is not equal to inhalation uptake. A subsequent fraction of the chemicals that reach the lungs can be absorbed into the blood stream and become bioavailable (uptake), while a fraction is also exhaled back into the air. The fraction reaching the blood and distributing amongst internal organs depends on various physiochemical properties and pharmacokinetics (Tronde et al., 2003), and is out of the scope of this review which focuses on intake at the exposure interface, which is the reference for most exposure assessments. Different methods of varying complexity can be used to determine f_{dep} . For inhaled gas-phase chemicals, f_{dep} is generally assumed to be 1 (Delmaar et al., 2005; Glen et al., 2012; Isaacs et al., 2014; Little et al., 2012; Shin et al., 2015b; Shin et al., 2012; Wenger et al., 2012; Zhang et al., 2014), meaning 100% reaches the lung alveoli. For particulates, several studies also assumed a f_{inh} of 1 for simplicity (Isaacs et al., 2014; Little et al., 2012; Shin et al., 2015b; Shin et al., 2012; Wenger et al., 2012). However, for inhalation of particulates, the value of f_{dep} depends on the size of the particles. Larger particles will mostly deposit in the upper regions of the respiratory tract and will be cleared via physical mechanisms or the gastrointestinal tract; in contrast, smaller particles tend to penetrate deeper in the respiratory tract and deposit in the alveolar region of the lungs (Delmaar et al., 2005; Lippmann, 2011; Yeh et al., 1996). Modeling approaches estimate the f_{dep} using a variety of accuracies. Users of the modeling software ConsExpo can define a particle diameter below which inhaled particles are assumed to reach the alveolar area of the lungs (Delmaar et al., 2005), where ConsExpo recommends a value

around 10-15 μm (Delmaar et al., 2005). Zhang et al. (Zhang et al., 2014) assigned a different value of f_{dep} for five different particle size ranges. In more complex approaches, a continuous particle size distribution can be combined with a continuous curve of f_{dep} (Humbert, 2009; Yeh et al., 1996) and be integrated over the particle size to obtain the inhalation exposure of particles. This latter method requires knowledge about the full particle size distribution in a particular consumer product use scenario, which is likely difficult to obtain information.

Key parameters and data availability

Key parameters to calculate the transfer to respiratory tract include the inhalation rate IR_{inh} (system-specific), exposure duration t_{inh} (product-specific), and bulk chemical concentration in air C_{air} (chemical-specific). The inhalation rate for the average population or for specific age and gender can be obtained e.g. from the U.S. EPA exposure factors handbook (USEPA, 2011). The relevant inhalation exposure duration will be specific to the product (Delmaar et al., 2005; Isaacs et al., 2014); for example products used within the shower may have a short exposure duration of only several minutes, whereas products that are household fixtures may lead to slow air releases exposing household occupants throughout their daily time spent indoors.

C_{air} can be calculated by dividing the mass of chemical released to air by the room volume, or to be more accurate, can be calculated from an indoor air model which considers the effects of air ventilation, sorption to surfaces, air degradation, gas-particle partitioning and/or imperfect mixing of the indoor air, as discussed in Section 3.5.2.

Applicability for LCA, CAA and HTS

The model for calculating the transfer to respiratory tract (inhalation exposure) is simple and straightforward, and the key parameters are readily available, so the model can be easily implemented in LCA, CAA and HTS.

4.2 Transfer to gastrointestinal tract

4.2.1 Dietary ingestion

Existing models

People can be exposed to chemicals such as additives, preservatives, or pesticide residues, via consumer products intended for direct ingestion, which describes the transfer from “food and beverages” to “GI tract”, i.e. the gastrointestinal tract (Figure 1). Exposure due to direct ingestion can be estimated as (Delmaar et al., 2005; Isaacs et al., 2014; Shin et al., 2015b), which assumes that all chemicals within food or beverages will reach the GI tract:

$$m_{ing} = IR_{food} \cdot f_w \cdot 10^6 \quad (4.2-1)$$

where m_{ing} is the chemical mass that is transferred to the GI tract via dietary ingestion (μg), IR_{food} is the ingested amount of a certain type of food or dietary supplement in a certain duration (g), and f_w is the weight fraction of the chemical in the product (food, beverages, or dietary supplement).

Key parameters and data availability

Concentration or weight fraction of chemicals in the food f_w is a key chemical-specific parameter influencing ingestion-related exposure to food and beverages. The weight fraction of chemical additives or preservatives may be inferred from the ingredient lists or the maximum use levels in food additive standards (2015). If f_w is unknown, it may be measured, estimated, or modeled. We provide some examples of methods and considerations used to determine f_w which can be used as input to Eq. 4.2-1. For pesticide residues, many studies have measured their concentrations in various food samples (Lu et al., 2010; Nougadère et al., 2012; Schechter et al., 2010; Tusa et al., 2009) which can be used as the data source. Alternatively, concentrations of pesticide residues in food can be modelled according to Fantke et al. (Fantke et al., 2011a; Fantke et al., 2012a; Fantke et al., 2011b; Fantke et al., 2012b) and are made available for LCA calculation for more than 800 pesticides (Fantke and Jolliet, 2015) with food processing contributing as a loss factor for residues between crop harvest and consumed processed food. When modeling the key parameter f_w , dissipation of chemicals from food and food processing need to be considered as important loss factors which will affect the final chemical concentrations in food available for human consumption. Dissipation from food is investigated mostly for pesticides (Fantke et al., 2014; Fantke and Juraske, 2013), where it has been shown that degradation is the predominant process contributing to dissipation from food crops (Fantke et al., 2013; Jacobsen et al., 2015). Food processing is important for either intentionally added chemicals (e.g. fragrances) or unintentional residues (e.g. pesticides). Food processing factors differ in fact between chemicals and processing step (e.g. cooking, baking, or washing), but are currently mostly available for different processing steps across chemicals and not specific for many chemicals (Kaushik et al., 2009; Keikotlhaile et al., 2010; Liang et al., 2014).

Another important parameter is the food consumption amount, which depends both on the consumer and the type of food, so it is system- and product-specific. Food consumption data can be found in databases like FAOSTAT (<http://faostat.fao.org/site/609/default.aspx#ancor>) and NHANES (<http://www.cdc.gov/nchs/nhanes.htm>). Another way is estimate the food consumption rate from the quantity of food purchased, but in this case the fraction of food waste may substantially influence the actual quantity of food consumed, and thus of chemical mass ingested (Isaacs et al., 2014).

Applicability for LCA, CAA and HTS

The model for calculating the transfer to GI tract via dietary ingestion is simple and straightforward, and the key parameters are readily available, so the model can be easily implemented in LCA, CAA and HTS.

4.2.2 Non-dietary ingestion

Non-dietary ingestion primarily occurs through hand-to-mouth or object-to-mouth contact. Children's exposure to various chemicals, such as phthalates, arsenic and BPA, from hand-to-mouth contact has been documented in recent studies (Geens et al., 2009; Little et al., 2012; Zartarian et al., 2006). Younger children also have documented frequent object-to-mouth behaviors, such as mouthing and chewing toys or other objects. Adults can also have hand- or object-to-mouth contacts such as incidental ingestion during eating, nail biting or using plastic utensils. These transfer pathways are especially important for SVOCs, which tend to sorb strongly on dust particles and surfaces; for example, exposure to PBDEs by non-dietary ingestion may be more significant than dietary exposure (Stapleton et al., 2008). Transfers to the mouth are typically assumed to be carried by saliva to the GI tract without degradation or other loss, although in some cases children's drool has been taken into account (Delmaar et al., 2005).

Existing models

Non-dietary ingestion can happen through two identified pathways, one is the transfer of chemicals from hand/object surfaces to the mouth, and the other is the transfer of chemicals from within object interior to the mouth. Different models are required to estimate the transfers through these two pathways.

For the transfer of chemicals from hand/object surfaces to the mouth, the removal efficiency approach is a commonly used method, where upon contact with the mouth chemicals on the surfaces are transferred by a fixed fraction (removal efficiency). For hand-to-mouth, this fraction depends on the fraction of hands being mouthed and contact frequency (Eq. 4.2-2). This method was used in the US EPA's SHEDS-MM and SHEDS-HT frameworks (Glen et al., 2012; Isaacs et al., 2014), and in several studies estimating exposure to various VOCs and SVOCs (Shin et al., 2012; Stapleton et al., 2008; Trudel et al., 2008). Similarly, exposure to chemicals on object surfaces from object-to-mouth contacts has been estimated as a function of the chemical mass per area on the object surface, the object area being mouthed, a fixed transfer fraction and contact frequency (Eq. 4.2-3). From the perspective of compartmental modeling for chemicals within consumer objects, these approaches require information on the transfer of chemicals within the product to its own product surface as well as to other object surfaces and hand surfaces e.g. through dust or intentional application.

While the above two methods estimate the exposures from mouthing contact with the hands or a specific object, another approach can be used to assess the overall non-dietary ingestion exposure from dust particles deposited on hands and various object surfaces. This approach quantifies the overall dust ingestion (Geens et al., 2009; Little et al., 2012), which is expressed as the product of the chemical concentration in dust and the overall dust ingestion rate (Eq. 4.2-4). This estimate will include dust ingestions from various activities such as hand-to-mouth contact, object-to-mouth contact, and consumption of dust-contaminated food. However, its disadvantage is that exposure from each specific activity cannot be differentiated, and that this method cannot account for the exposures from the ingestion of chemicals that are not associated with dust, such as chemicals that are directly applied on object surfaces as solutions.

For the transfer of chemicals from within object interior to the mouth, a migration rate approach can be used to describe the leaching of a chemical from an object (e.g., a pacifier) to the saliva in mouth (Eq. 4.2-5a) (Delmaar et al., 2005). This approach assumes that the migration rate changes through time depending on the chemical mass remaining in the object. If the chemical loss from the object due to such transfer is negligible, then we propose that the migration rate can be assumed constant, and thus the migration rate approach can be simplified as Eq. 4.2-5b.

Table 9. Equations to model the transfer of chemicals to the gastrointestinal tract via non-dietary ingestion

Transfer of chemicals from object or hand surfaces to GI tract

(1) Removal efficiency approach for hand-to-mouth

$$m_{hm} = SC_{hand} \times A_{hand} \times (1 - (1 - f_{hm} \times TE_{hm})^{t_{hm} \cdot FQ_{hm}}) \quad (4.2-2)$$

(2) Removal efficiency approach for object-to-mouth

$$m_{om} = SC_{obj} \times A_{om} \times TE_{om} \times FQ_{om} \quad (4.2-3)$$

(3) Dust ingestion approach

$$m_{mouth} = C_{dust} \cdot IR_{dust} \quad (4.2-4)$$

Transfer of chemicals from within an object to GI tract

Migration rate approach:

$$m_{om} = M_{om} \cdot f_w \cdot (1 - \exp(-\frac{J_{om} \times A_{om}}{M_{om} \times f_w} \times t_{om})) \quad (4.2-5a)$$

*Simplified version (proposed by us):

$$m_{om} = J_{om} \cdot A_{om} \cdot t_{om} \quad (4.2-5b)$$

1409 A_{hand} - area of the hands (m^2), A_{om} - area of the object that enters the mouth (m^2), C_{dust} - chemical concentration in the dust
1410 ($\mu g/mg$), m_{hm} - chemical mass that is transferred to the GI tract via hand-to-mouth contact (μg), m_{om} - Chemical mass that is
1411 transferred to the GI tract via object-to-mouth contact (μg), m_{mouth} - chemical mass that is transferred to the GI tract via non-
1412 dietary ingestion (μg), N_{hm} - number of hand-to-mouth contact events (unitless), N_{om} - number of object-to-mouth contact
1413 events (unitless), f_{hm} - fraction of the hands that enter the mouth (unitless), f_w - weight fraction of the chemical in the object,
1414 IR_{dust} - overall dust ingestion amount in a certain duration (mg/l), J_{om} - initial migration rate at which the chemical migrates from
1415 the object ($kg/m^2/s$), M_{om} - total amount of object that is being mouthed (kg), SC_{hand} - chemical mass per area on the hand
1416 surface ($\mu g/m^2$), SC_{obj} - chemical mass per areon the object surface ($\mu g/m^2$), TE_{hm} - hand-to-mouth removal efficiency (nitless),
1417 TE_{om} - object-to-mouth removal efficiency (unitless), t_{om} - hand-to-mouth duration (s).

1418

1419 Key parameters and data availability

1420 For the removal efficiency approaches (Eqs. 4.2-2 and 4.2-3), chemical-specific parameters include the
1421 chemical mass per area on the hands (SC_{hand}) or on the object surface (SC_{obj}), as well as the mouthing
1422 removal efficiencies through hand- and object-to-mouth (TE_{hm} and TE_{om}). The chemical concentration on
1423 the hands or object surface can be measured using surface wipe samples (Stapleton et al., 2008;
1424 Watkins et al., 2011) or predicted using mathematical models. The methods used to derive the chemical
1425 mass per area on object surfaces are discussed in Section 3.3.2. For the mouthing removal efficiencies,
1426 they are typically assumed as 0.5 (i.e. 50%) without reliable data (Stapleton et al., 2008) or equal to the
1427 hand washing removal efficiency (Isaacs et al., 2014; Zartarian et al., 2006).

1428 The only product-specific parameter for the removal efficiency approaches is the object area that enters
1429 the mouth (A_{om}) for object-to-mouth exposure. An area on the scale of 45 to 50 cm^2 , which is a ping-
1430 pong ball's surface area, has been commonly used (Glen et al., 2012).

1431 System-specific parameters for the removal efficiency approaches include the contact frequencies and
1432 relevant hand areas. Hand-to-mouth contact frequencies for various age groups can be obtained e.g.
1433 from the U.S. EPA exposure factors handbook (USEPA, 2011). Empirical evidence suggests that children's
1434 hand- and object-to-mouth frequencies are best described by Weibull distributions (Isaacs et al., 2014;
1435 Xue et al., 2007; Xue et al., 2010) and the fraction of mouthed hand area by a beta distribution reflecting
1436 event-to-event variability (Zartarian et al., 2006), although the fraction can also be set to a single value
1437 e.g., of 0.1 (Stapleton et al., 2008).

1438 For the dust ingestion approach (Eq. 4.2-4), only two parameters are needed – the chemical
1439 concentration in dust (chemical-specific) and the overall dust ingestion rate (system-specific). The
1440 chemical concentration in dust can be predicted by well-developed multimedia indoor models (Little et
1441 al., 2012; Shin et al., 2013) or be obtained from measurements (Blanchard et al., 2014; Geens et al.,

2009; Weschler and Nazaroff, 2008). The overall dust ingestion rates for different age groups from infants to adults have been estimated by several studies, which are based on tracer-element-based mass-balance studies (Geens et al., 2009; Little et al., 2012; Özkaynak et al., 2011; Trudel et al., 2008) or time-activity modeling (Özkaynak et al., 2011).

For chemicals leaching from within the object when the object is mouthed, the migration rate J_{om} is a key parameter (Eq. 4.2-5), which is chemical- and product-specific. J_{om} has been estimated through several experimental studies, e.g. with volunteers or machines simulating the mouthing of objects and measuring the concentrations of SVOCs in saliva or saliva simulant (Earls et al., 2003; Niino et al., 2003; Niino et al., 2002; Steiner et al., 1998).

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, the removal efficiency approaches for chemicals on object or skin surface (Eqs. 4.2-2 & 3) are simple multiplications and can account for the product-chemical characteristics. However, the lack of data for mouthing removal efficiencies may prevent the high-throughput use of these models. These removal efficiencies are product-chemical specific, so assuming a generic value is not satisfactory. Experimental data or prediction methods for mouthing removal efficiencies need to be obtained or developed for better estimates using these models. Similar problems exist for the migration rate approach (Eq. 4.2-5) for chemicals within a solid object, where migration rates for more product-chemical combinations would need to be determined empirically, or a mechanistic method considering chemical and object properties would need to be developed. The dust ingestion approach (Eq. 4.2-4) is the simplest, and its required input parameters can be readily obtained or predicted. However, as mentioned above, this approach cannot differentiate the dust ingestion exposure from each specific activity or specific object, and it cannot account for the exposures from the non-dietary ingestion of chemicals that are not associated with dust. Thus, the dust ingestion approach is more suitable for use as a best-case estimate of the overall non-dietary ingestion exposure for assessments of aggregated instead of product-specific exposures.

4.3 Transfer to epidermis

Existing models

This section reviews models used to estimate transfer to the epidermis from the skin surface. Chemicals may be present on the skin surface due to passive partitioning from air, incidental contact with household products such as cleaning solutions, contact with solid objects, or intentional application of a cosmetic or personal care products (Csiszar et al., 2016; Delmaar et al., 2005; Isaacs et al., 2014; Weschler and Nazaroff, 2013). The skin is a complex organ with several different layers and sublayers. However, to be consistent with the inhalation and ingestion exposure routes, where exposure metrics are in relation to the contact interface (e.g. the respiratory and gastrointestinal tracts), we define dermal exposure as penetration of chemical through the first epidermal sublayer (i.e. the stratum corneum) where a chemical can be further transported into deeper skin layers and the rest of the body (Dumont et al., 2015).

The most simplistic models used to estimate skin permeation assume that a fixed fraction of chemical on the skin surface permeates into the skin, hereafter referred to as the absorption fraction. For example, Gosens et al. (Gosens et al., 2014) use a multiplicative absorption fraction derived from the literature to estimate dermal exposure to parabens in personal care products. The SHEDS-HT model

(Isaacs et al., 2014) uses a similar approach, however linearly scales a fixed absorption fraction by the ratio of the chemical-specific skin permeation coefficient, K_p (estimated using DERMWIN QSAR models within EPISuite (USEPA, 2012)) to the K_p for permethrin, a well-studied reference compound. This method is computationally simple; however, as noted by Isaacs et al (Isaacs et al., 2014) is an unqualified simplifying assumption.

More complicated than fixed absorption fractions, skin permeation models based on mass balances may improve chemical-specific and time-dependent accuracy. For example, Delmaar et al (Delmaar et al., 2015) solved a chemical mass balance as a function of K_p and exposure duration to estimate the absorption fraction, which excluded competing volatilization to air. Ernstoff et al. (Ernstoff et al., 2016) present a model similar to Delmaar et al. (Delmaar et al., 2015), but included volatilization as a competing factor (Eqs. 4.3-1a to 1c), and simplifying it into an analytical solution for the fractional mass transferred to skin, f_{ms} (Eq 4.3-2). More details of these mass balance model has been presented in Section 3.4.1.

To model dermal permeation of chemicals suspended in air, Weschler and Nazaroff (Weschler and Nazaroff, 2012) also use a mass balance approach using equilibrium relationships between air, the lipids on the skin surface, and the SVOC dissolved in water. They assume that the chemical concentration in skin surface lipid is in equilibrium with the concentration in air related by a gas-phase to skin lipid partition coefficient (Weschler and Nazaroff, 2012), which is also employed by EPA's latest CEM model (USEPA, 2015). Multi-dimensional diffusion models have also been developed for example in medical and occupational exposure research, which can consider non-steady-state kinetics and various skin compartments and transfers (Naegel et al., 2013); due to their complexity and specific applications such models remain outside of the scope of this review.

Table 10. Equations to model the transfer of chemicals to epidermis

Ernstoff et al.'s mass balance model

(1) Mass balance equations:

$$\frac{dm_p}{dt} = -m_p (k_{ps} + k_{pa}) \quad (4.3-1a)$$

$$\frac{dm_s}{dt} = k_{ps} m_p \quad (4.3-1b)$$

$$\frac{dm_a}{dt} = k_{pa} m_p \quad (4.3-1c)$$

(2) Solution for the fractional mass transferred to epidermis at time t :

$$f_{ms} = \frac{k_{ps}}{k_{ps} + k_{pa}} (1 - e^{-(k_{ps} + k_{pa})t}) \quad (4.3-2)$$

* k_{ps} is a function of the skin permeation coefficient K_p and the thickness of the product on the skin.

Key parameter: K_p

(1) Potts and Guy method:

$$K_p = 10^{-6.3 + 0.71 \log K_{ow} - 0.0061 \cdot MW_c} \cdot 10^{-2} \quad (4.3-3)$$

(2) ten Berge 2009 method:

$$K_p = (10^{-2.59+0.7318 \cdot \log K_{ow}-0.006832 \cdot MW_c} + \frac{0.043}{MW_c^{1.361}}) \cdot \frac{10^{-2}}{3600} \quad (4.3-4)$$

(3) ten Berge 2010 method (based on Wilschut 1995) as documented by Brown et al. 2016:

$$K_p = 10^{\frac{1}{\frac{1}{K_{psc}} + \frac{1}{K_{pol}} + \frac{1}{K_{aq}}}} \cdot \frac{10^{-2}}{3600} \quad (4.3-5a)$$

$$K_{psc} = 10^{-2.69+0.981 \cdot \log K_{ow}-0.0079 \cdot MW_c} \quad (4.3-5b)$$

$$K_{pol} = \frac{0.0552}{MW_c^{1.38}} \quad (4.3-5c)$$

$$K_{aq} = \frac{1121}{MW_c^{1.96}} \quad (4.3-5d)$$

f_{msl} - fraction of chemical mass that is transferred into skin epidermis (unitless), K_{ow} - octanol-water partition coefficient (unitless), K_p - skin permeation coefficient (m/s), K_{psc} - permeation coefficient of the lipid fraction of stratum corneum (cm/h), K_{pol} - permeation coefficient of the protein fraction of stratum corneum (cm/h), K_{aq} - permeation coefficient of the watery epidermal layer (cm/h), k_{ps} - rate constant for transfer from the product on skin surface into the skin (s^{-1}), k_{po} - rate constant for transfer from the product on skin surface into the air (s^{-1}), MW_c - chemical's molecular weight (g/mol), m_p - chemical mass in the product that is applied to skin surface (μg), m_s - chemical mass in skin (μg), m_a - chemical mass in air (μg), 10^{-2} - conversion factor from cm to m, $10^{-2}/3600$ - conversion factor from cm/h to m/s.

Key parameters and data availability

In general, the skin permeation models identified are based on the chemical-specific skin permeation coefficient K_p (m/s) which describes the rate of transfer of one chemical from an occluded vehicle solution on the skin (usually water) into the stratum corneum. To date, skin permeation coefficient QSAR models focus on binary solutions, and there is limited information on how to consistently incorporate other parameters accounting for effects of product formulations, mixtures, and solvent evaporation (Karadzovska et al., 2013). Csiszar et al. 2016 (Csiszar et al., 2016), for example, partially accounted mixtures by stochastically modeling variability in K_p based on the addition of co-solvents. A number of skin permeation coefficients for aqueous solutions has been measured for various chemicals (Guy and Hadgraft, 2003), and following these data a number of Quantitative Structure-Permeability Relationships (QSPRs) or QSARs have been developed to predict K_p for aqueous solutions based on physicochemical properties (Mitragotri et al., 2011). EPISuite (USEPA, 2012), for example, predicts chemical-specific K_p using a modification of the most commonly used Potts and Guy (Potts and Guy, 1992) QSPR (Eq. 4.3-3). Although this QSPR is a commonly used model, recent reviews and evaluations of QSPR models against *in vitro* data found models by ten Berge (ten Berge, 2009; ten Berge, 2010) to be the best predictors of K_p (Brown et al., 2016; Ernstoff et al., 2016), specifically the ten Berge 2009 model (ten Berge, 2009) (Eq. 4.3-4) and the ten Berge 2010 model (ten Berge, 2010) updating a previous model by Wilschut et al. (Wilschut et al., 1995) (Eqs. 4.3-5a to 5d) are recommended.

Applicability for LCA, CAA and HTS

In terms of the applicability for LCA, CAA and HTS, the most complex skin permeation models require numeric solutions and often distinguish between various skin layers, which are typically beyond the scope of exposure estimates within LCA, CAA and HTS that do not account for physiologically based pharmacokinetic modeling. Kasting et al. (Kasting et al., 2008) operationalize such a complex numeric model for risk assessment practitioners in a spreadsheet, but it remains operational for only one compound at a time and requires various input physicochemical properties. Therefore, the models that

require a limited number of physicochemical properties (i.e. MW , K_{ow} , and K_{ow}) are more applicable for LCA and HTS, such as the models presented by Delmaar et al. (Delmaar et al., 2015) for non-volatile chemicals, and Ernstoff et al. (Ernstoff et al., 2016). Further, when applying such models to product based assessments, other factors may influence exposure, for example diluting a product with wash water. Although the limitations of these models remain, especially with regards to complex chemical mixtures and ionization, such information is so far lacking to improve modeling efforts at a larger scale, e.g. for many types of cosmetic formulations (Isaacs et al., 2014).

5. Summary and recommendation

Table 11 summarizes the potential models suited for LCA, CAA and HTS, their main strengths and limitations, as well as the required key model input parameters, and future model development needs for each reviewed transfer process or pathway. Out of the 15 transfer pathways reviewed, 8 pathways are considered as highly mature to be recommended as suitable starting points for use in LCA, CAA and HTS approaches: transfer of chemicals from article interior to indoor air (Section 3.1.1), transfer of chemicals from the inner space of an appliance to indoor air (Section 3.2.1), transfer of chemicals from object surfaces to indoor air (Section 3.3.1), transfer of chemicals from skin surface to indoor air (Section 3.4.1), transfer of chemicals in sprays (Section 3.5.1), indoor transport and fate processes (Section 3.5.2), transfer to respiratory tract (Section 4.1), and dietary transfer to gastrointestinal tract (Section 4.2.1). For these high-maturity pathways, detailed mechanistic models have been developed, and future developments generally should include simplification of the complex existing models to make them more applicable for HT analysis, such as making analytical solutions possible. Four transfer pathways, namely the transfer of chemicals from article interior to food and beverages (Section 3.1.2), transfer of chemicals from object surfaces to skin surface (Section 3.3.2), non-dietary transfer to the gastrointestinal tract (Section 4.2.2), and transfer of chemicals from skin surface to epidermis (Section 4.3) are considered to have medium maturity. For these three pathways, models are only validated for certain types of products or the key parameters are only available for limited product-chemical combinations. In order to better include these pathways into LCA, CAA and HTS, models need to be generalized/extended to be applicable to more product types and/or more generalized QSAR methods need to be developed to predict the key parameters. Finally, three transfer pathways are considered immature, including the transfer of chemicals from article interior to skin surface (Section 3.1.3) and to object surface (Section 3.1.4), as well as the transfer of chemicals from the inner space of an appliance to object surfaces (Section 3.2.2). Very few existing models are available to predict these transfers, or the existing models require chemical specific parameters which cannot be predicted by currently available QSAR methods. It should also be noted that the six compartments and 15 transfer pathways covered in this review are not a comprehensive representation of all near-field compartments and transfer pathways. The modeling of near-field exposures may be extended to include additional compartments or transfer pathways, such as a pool of liquid (e.g., bathtub, hand washing clothes or dishes, etc.), which can be a focus of future research efforts. In addition, many consumer products need to be mixed, diluted, loaded into an appliance or in some other way handled before the intended use. During such handling processes, various chemical transfers can happen which can lead to human exposures, for example inhalation exposures due to air releases or dermal exposures due to incidental spills. Such mixing and loading transfers are not covered in this review, but useful information about these transfers can be found in ConsExpo factsheets (Bremmer et al., 2006a; Bremmer and Engelen, 2007; Lodder et al., 2006a; Lodder et al., 2006c). In conclusion, substantial efforts need to be devoted to

understanding the contribution of various pathways to the overall near-field exposures and to make them available in LCA, CAA and HTS approaches. If their contributions can be demonstrated to be significant for overall human exposure to chemicals in consumer products, then future development of more accurate models is warranted.

Data availability is another important aspect for modeling near-field exposures, since models require data for validation and also for certain parameters. Generally, the key parameters required depend both on the chemical and the product material or composition. A major challenge of applying models in LCA, CAA and HTS practices is the availability of key parameters across a wide range of chemical-product combinations. Even for the transfer pathways with high maturity, experimental data or mathematical methods are only available to estimate the key parameters for certain chemical-product combinations. However, most chemicals still lack several types of data required for modeling the various near-field transfer processes and pathways, whereas most data are currently available for classical persistent organic pollutants (POPs), such as dioxins, for metals, and for organic pesticides. Therefore, future research may focus on two directions: (1) the development of extended QSARs which are capable of estimating the key parameters for a broader range of chemical-product combinations; and (2) the development of guidance on the best models to use for specific chemical-product combinations. In addition, additional data on exposure factors are needed for population-scale near-field exposure assessments, since there are significant variations in exposure factors within and between populations. Examples of exposure factors include consumption rates of various types of foods, product use frequencies, amounts of products used, dermal/hand contact frequencies, hand/object-to-mouth frequencies and household characteristics such as room air, flooring area and ventilation rate. Such data are well available for certain types of products and certain population groups but not for the others; for example, many data exist for hand-to-mouth frequencies for children while few data are available for adults. Moreover, another major limitation of data availability is related to product-chemical combination and chemical contents, as very limited data are available for the mapping of chemicals to product types and the actual chemical concentrations in products, which are very influential parameters for model estimated chemical emissions and exposures. Therefore, more comprehensive datasets on exposure factors and chemical information could help inform LCA, CAA and HTS modeling approaches.

As previously mentioned, a motivation for this review is to facilitate the inclusion of near-field exposure modeling in LCA, CAA, and HTS for more comprehensive assessments that include potentially dominating pathways. It is important, however, that exposure models are developed, for example, building on and adapting the models described in this review, to handle data availabilities (i.e. relying on readily available physicochemical properties) and that data burden is also being addressed in parallel. Obtaining accurate physicochemical properties for more chemicals and concentrations of chemicals in products is a concern for both near- and far-field exposure assessments, and are thus addressed in various modeling and data collection efforts (Goldsmith et al., 2014; Guo, 2002; USEPA, 2012). In addition to chemical-specific data, when screening many different product categories at once, there are substantial overlaps in required exposure scenario data, such as average hand-to-mouth frequency for infants or room ventilations rates. To date, there are several important sources of information for estimating such exposure modeling parameters for various exposure scenario parameters (Comiskey et al., 2015; Delmaar et al., 2005; Isaacs et al., 2014; USEPA, 2011; Xue et al., 2007; Xue et al., 2010), which will be valuable to decrease data burdens.

While the present review has summarized existing models for individual near-field pathways, another key piece is the integration of these pathways. Many of the models reviewed in this paper belong to larger modeling suites covering multi-pathway exposures (e.g. SHEDS-HT, ConsExpo, EFAST-

CEM)(Delmaar et al., 2005; Isaacs et al., 2014; USEPA, 2015), and an important next step is to assess integration methods. The existing models for various transfer pathways have very different mathematical formats and data needs, which render it currently difficult to assess the near-field exposures from all pathways in a consistent way. In addition, for certain immature pathways completely new models need to be developed. As a result, we see a need of developing a framework that consistently integrates the various near-field pathways, and also consistently couples the near-field and far-field exposures models for comparative exposure assessments in LCA, CAA and HTS. Such a framework should have the ability to integrate newly developed models for the immature pathways once they become available. These frameworks should employ models that reflect the main transfer processes, while being simple enough for HT analysis. Recently, Fantke et al. have developed a matrix-based framework fulfilling these requirements, (Fantke et al., 2016). MERLIN-Expo, an integrated multimedia exposure assessment tool which primarily deals with far-field exposures (Ciffroy et al., 2016a), has also been recently proposed to include exposures to consumer chemicals, (Suciu et al., 2016).

The process of this review discovered pervasive inconsistencies in model documentation (e.g. theory, structure, parameterization and applicability) which poses a barrier to adapting models for use in a consistent exposure framework. When new models are created, or existing models are documented, we recommend consulting recent suggestions for a standard documentation protocol (SDP) that can facilitate transparency and use of models by third-party users (Ciffroy et al., 2016b).

Table 11. Summary of potential LCA-, CAA- or HTS-suited models for the reviewed near-field transfer pathways (see attached document)

Acknowledgements

Funding for this research was provided by US EPA contract EP-14-C-000115 on Development of Modular Risk Pathway Descriptions for Life Cycle Assessment and by the Marie Curie project Quan-Tox (grant agreement no. 631910) funded by the European Commission under the Seventh Framework Programme. This research was supported in part by an appointment of S. Csiszar to the Postdoctoral Research Program at the National Risk Management Research Laboratory, U.S. EPA administered by the Oak Ridge Institute for Science and Education through Interagency Agreement No. DW-89-92298301 between the U.S. Department of Energy and the U.S. Environmental Protection Agency.

The views expressed in this article are those of the authors and do not necessarily represent the views or policies of the U.S. Environmental Protection Agency.

References

- CODEX GENERAL STANDARD FOR FOOD ADDITIVES (GSFA) ONLINE DATABASE. Codex Alimentarius Commission, Food and Agriculture Organization of the United Nations, World Health Organization, 2015.
- Api AM, Bredbenner A, McGowen M, Niemiera D, Parker L, Renskers K, et al. Skin contact transfer of three fragrance residues from candles to human hands. *Regulatory Toxicology and Pharmacology* 2007; 48: 279-283.
- AuYeung W, Canales RA, Beamer P, Ferguson AC, Leckie JO. Young children's hand contact activities: An observational study via videotaping in primarily outdoor residential settings. *Journal of Exposure Science and Environmental Epidemiology* 2006; 16: 434-446.
- Begley T, Castle L, Feigenbaum A, Franz R, Hinrichs K, Lickly T, et al. Evaluation of migration models that might be used in support of regulations for food-contact plastics. *Food Additives and Contaminants* 2005; 22: 73-90.
- Bennett DH, Furtaw EJ. Fugacity-based indoor residential pesticide fate model. *Environmental science & technology* 2004; 38: 2142-2152.
- Blanchard O, Glorennec P, Mercier F, Bonvallot N, Chevrier C, Ramalho O, et al. Semivolatile organic compounds in indoor air and settled dust in 30 French dwellings. *Environmental science & technology* 2014; 48: 3959-3969.
- Blondeau P, Tiffonnet A, Damian A, Amiri O, Molina J. Assessment of contaminant diffusivities in building materials from porosimetry tests. *Indoor Air* 2003; 13: 310-318.
- Bremmer HJ, Blom WM, Hoeven-Arentzen PHv, Lodder LCHPhd, Raaij MTMv, Straetmans EHFM, et al. ConsExpo 4.0: Pest Control Products Fact Sheet, 2006a.
- Bremmer HJ, Engelen JGMv. ConsExpo 4.0: Paint Products Fact Sheet, 2007.
- Bremmer HJ, Lodder LCHPhd, Engelen JGMv. ConsExpo 4.0: Cosmetics Fact Sheet, 2006b.
- Brown TN, Armitage JM, Egeghy P, Kircanski I, Arnot JA. Dermal permeation data and models for the prioritization and screening-level exposure assessment of organic chemicals. *Environment International* 2016; In press.
- Chen F, Simon C, Lai AC. Modeling particle distribution and deposition in indoor environments with a new drift-flux model. *Atmospheric Environment* 2006; 40: 357-367.
- Ciffroy P, Alfonso B, Altenpohl A, Banjac Z, Bierkens J, Brochot C, et al. Modelling the exposure to chemicals for risk assessment: a comprehensive library of multimedia and PBPK models for integration, prediction, uncertainty and sensitivity analysis – the MERLIN-Expo tool. *Science of The Total Environment* 2016a.
- Ciffroy P, Altenpohl A, Fait G, Fransman W, Paini A, Radovnikovic A, et al. Development of a standard documentation protocol for communicating exposure models. *Science of The Total Environment* 2016b.
- Cohen Hubal EA, Nishioka MG, Ivancic WA, Morara M, Egeghy PP. Comparing surface residue transfer efficiencies to hands using polar and nonpolar fluorescent tracers. *Environmental science & technology* 2007; 42: 934-939.
- Comiskey D, Api A, Barratt C, Daly E, Ellis G, McNamara C, et al. Novel database for exposure to fragrance ingredients in cosmetics and personal care products. *Regulatory Toxicology and Pharmacology* 2015.
- Corea NV, Basketter DA, Clapp C, Van Asten A, Marty JP, Pons-Guiraud A, et al. Fragrance allergy: assessing the risk from washed fabrics. *Contact dermatitis* 2006; 55: 48-53.
- CPSC. Review of Exposure Data and Assessments for Select Dialkyl Ortho-Phthalates. U.S. Consumer Product Safety Commission (CPSC), Bethesda, MD, 2010.
- Crank J. *The Mathematics of Diffusion*: 2d Ed: Clarendon Press, 1975.

- Csiszar SA, Ernstoff AS, Fantke P, Jolliet O. Stochastic modeling of near-field exposure to parabens in personal care products. *Journal of Exposure Science and Environmental Epidemiology* 2016.
- Delmaar C, Bokkers B, ter Burg W, Schuur G. Validation of an aggregate exposure model for substances in consumer products: a case study of diethyl phthalate in personal care products. *Journal of Exposure Science and Environmental Epidemiology* 2015; 25: 317-323.
- Delmaar J, Bokkers B, Ter Burg W, van Engelen J. First tier modeling of consumer dermal exposure to substances in consumer articles under REACH: A quantitative evaluation of the ECETOC TRA for consumers tool. *Regulatory Toxicology and Pharmacology* 2013; 65: 79-86.
- Delmaar JE, Park MVDZ, Engelen JGMv. ConsExpo 4.0: Consumer Exposure and Uptake Models Program Manual, 2005.
- Deng B, Kim CN. An analytical model for VOCs emission from dry building materials. *Atmospheric Environment* 2004; 38: 1173-1180.
- Deng B, Kim CN. CFD simulation of VOCs concentrations in a resident building with new carpet under different ventilation strategies. *Building and environment* 2007; 42: 297-303.
- Deng B, Tang S, Kim JT, Kim CN. Numerical modeling of volatile organic compound emissions from multi-layer dry building materials. *Korean Journal of Chemical Engineering* 2010; 27: 1049-1055.
- Dionisio KL, Frame AM, Goldsmith M-R, Wambaugh JF, Liddell A, Cathey T, et al. Exploring consumer exposure pathways and patterns of use for chemicals in the environment. *Toxicology Reports* 2015; 2: 228-237.
- Dudzina T, Hidalgo EG, von Goetz N, Bogdal C, Hungerbuehler K. Evaporation of decamethylcyclopentasiloxane (D5) from selected cosmetic products: Implications for consumer exposure modeling. *Environment international* 2015; 84: 55-63.
- Dumont C, Prieto P, Asturiol D, Worth A. Review of the Availability of In Vitro and In Silico Methods for Assessing Dermal Bioavailability. *Applied In Vitro Toxicology* 2015; 1: 147-164.
- Earls A, Axford I, Braybrook JHI. Gas chromatography–mass spectrometry determination of the migration of phthalate plasticisers from polyvinyl chloride toys and childcare articles. *Journal of chromatography A* 2003; 983: 237-246.
- Earnest CM, Corsi RL. Inhalation exposure to cleaning products: application of a two-zone model. *Journal of occupational and environmental hygiene* 2013; 10: 328-335.
- EC. CPNP Cosmetic Product Notification Portal, Article 13 User Manual, p. 214. European Commission, Brussels, Belgium, 2013.
- ECB. European Union Risk Assessment Report on Bis(2-Ethylhexyl) Phthalate (DEHP). 80. European Commission, Joint Research Centre, Institute of Health and Consumer Protection (IHCP), Toxicology and Chemical Substances (TCS), European Chemicals Bureau (ECB), 2008.
- ECHA. Guidance on information requirements and chemical safety assessment: consumer exposure estimation. (Chapter R.15). European Chemicals Agency (ECHA), 2010.
- ECHA. Guidance on information requirements and chemical safety assessment, Chapter R.14: Occupational exposure estimation. European Chemicals Agency, Helsinki, Finland, 2012.
- Ernstoff AS, Fantke P, Csiszar SA, Henderson AD, Chung S, Jolliet O. Multi-pathway exposure modelling of chemicals in cosmetics with application to shampoo. *Environmental International* 2016; Accepted.
- Fantke P, Charles R, de Alencastro LF, Friedrich R, Jolliet O. Plant uptake of pesticides and human health: dynamic modeling of residues in wheat and ingestion intake. *Chemosphere* 2011a; 85: 1639-1647.
- Fantke P, Ernstoff AS, Huang L, Csiszar SA, Jolliet O. Coupled near-field and far-field exposure assessment framework for chemicals in consumer products. *Environ. Int.* 2016; In press.
- Fantke P, Friedrich R, Jolliet O. Health impact and damage cost assessment of pesticides in Europe. *Environment international* 2012a; 49: 9-17.
- Fantke P, Gillespie BW, Juraske R, Jolliet O. Estimating half-lives for pesticide dissipation from plants. *Environmental science & technology* 2014; 48: 8588-8602.

- Fantke P, Jolliet O. Life cycle human health impacts of 875 pesticides. *The International Journal of Life Cycle Assessment* 2015; 1-12.
- Fantke P, Juraske R. Variability of pesticide dissipation half-lives in plants. *Environmental science & technology* 2013; 47: 3548-3562.
- Fantke P, Juraske R, Antón A, Friedrich R, Jolliet O. Dynamic multicrop model to characterize impacts of pesticides in food. *Environmental science & technology* 2011b; 45: 8842-8849.
- Fantke P, Weber R, Scheringer M. From incremental to fundamental substitution in chemical alternatives assessment. *Sustainable Chemistry and Pharmacy* 2015; 1: 1-8.
- Fantke P, Wieland P, Juraske R, Shaddick G, Itoiz ES, Friedrich R, et al. Parameterization models for pesticide exposure via crop consumption. *Environmental science & technology* 2012b; 46: 12864-12872.
- Fantke P, Wieland P, Wannaz C, Friedrich R, Jolliet O. Dynamics of pesticide uptake into plants: From system functioning to parsimonious modeling. *Environmental Modelling & Software* 2013; 40: 316-324.
- Freeman N, Jimenez M, Reed K, Gurunathan S, Edwards R, Roy A, et al. Quantitative analysis of children's microactivity patterns: The Minnesota Children's Pesticide Exposure Study. *Journal of exposure analysis and environmental epidemiology* 2000; 11: 501-509.
- Freeman NC, Hore P, Black K, Jimenez M, Sheldon L, Tulve N, et al. Contributions of children's activities to pesticide hand loadings following residential pesticide application. *Journal of Exposure Science and Environmental Epidemiology* 2005; 15: 81-88.
- Furtaw EJ, Pandian MD, Nelson DR, Behar JV. Modeling indoor air concentrations near emission sources in imperfectly mixed rooms. *Journal of the Air & Waste Management Association* 1996; 46: 861-868.
- Gangwal S, Reif DM, Mosher S, Egeghy PP, Wambaugh JF, Judson RS, et al. Incorporating exposure information into the toxicological prioritization index decision support framework. *Science of the total environment* 2012; 435: 316-325.
- Geens T, Roosens L, Neels H, Covaci A. Assessment of human exposure to Bisphenol-A, Triclosan and Tetrabromobisphenol-A through indoor dust intake in Belgium. *Chemosphere* 2009; 76: 755-760.
- Glen G, Zartarian V, Smith L, Xue J. SHEDS-Residential version 4 Technical Manual. US Environmental Protection Agency, Office of Research and Development, 2012.
- Goldsmith M-R, Grulke C, Brooks R, Transue T, Tan Y, Frame A, et al. Development of a consumer product ingredient database for chemical exposure screening and prioritization. *Food and chemical toxicology* 2014; 65: 269-279.
- Gosens I, Delmaar CJ, ter Burg W, de Heer C, Schuur AG. Aggregate exposure approaches for parabens in personal care products: a case assessment for children between 0 and 3 years old. *Journal of Exposure Science and Environmental Epidemiology* 2014; 24: 208-214.
- Guo Z. Review of indoor emission source models. Part 2. Parameter estimation. *Environment Pollution* 2002; 120: 551-564.
- Guo Z, Roache N. Overall mass transfer coefficient for pollutant emissions from small water pools under simulated indoor environmental conditions. *Annals of Occupational Hygiene* 2003; 47: 279-286.
- Guy RH, Hadgraft J. *Transdermal drug delivery*: Marcel Dekker, 2003.
- Hagendorfer H, Lorenz C, Kaegi R, Sinnet B, Gehrig R, Goetz NV, et al. Size-fractionated characterization and quantification of nanoparticle release rates from a consumer spray product containing engineered nanoparticles. *Journal of nanoparticle research* 2010; 12: 2481-2494.
- Haghighat F, Huang H, Lee C-S. Modeling approaches for indoor air VOC emissions from dry building materials—a review. *ASHRAE Transactions* 2005; 111: 635-645.
- Hellweg S, Demou E, Bruzzi R, Meijer A, Rosenbaum RK, Huijbregts MA, et al. Integrating human indoor air pollutant exposure within life cycle impact assessment. *Environmental science & technology* 2009; 43: 1670-1679.

- Hodas N, Loh M, Shin HM, Li D, Bennett D, McKone TE, et al. Indoor inhalation intake fractions of fine particulate matter: review of influencing factors. *Indoor air* 2015.
- Holmgren T, Persson L, Andersson PL, Haglund P. A generic emission model to predict release of organic substances from materials in consumer goods. *Science of the Total Environment* 2012; 437: 306-314.
- Howard-Reed C, Corsi RL, Moya J. Mass transfer of volatile organic compounds from drinking water to indoor air: the role of residential dishwashers. *Environmental science & technology* 1999; 33: 2266-2272.
- Howard C, Corsi RL. Volatilization of chemicals from drinking water to indoor air: the role of residential washing machines. *Journal of the Air & Waste Management Association* 1998; 48: 907-914.
- Hu H, Zhang Y, Wang X, Little J. An analytical mass transfer model for predicting VOC emissions from multi-layered building materials with convective surfaces on both sides. *International Journal of Heat and Mass Transfer* 2007; 50: 2069-2077.
- Huang H, Haghighat F. Modelling of volatile organic compounds emission from dry building materials. *Building and Environment* 2002; 37: 1349-1360.
- Huang L, Jolliet O. A parsimonious model for the release of chemicals encapsulated in products. *Atmospheric Environment* 2015; Minor revision.
- Humbert S. Geographically differentiated life-cycle impact assessment of human health. Engineering-Civil and Environmental Engineering. Ph.D. dissertation. University of California, Berkeley, Berkeley, CA, 2009.
- Hussein T, Glytsos T, Ondráček J, Dohányosová P, Ždímal V, Hämeri K, et al. Particle size characterization and emission rates during indoor activities in a house. *Atmospheric Environment* 2006; 40: 4285-4307.
- Isaacs KK, Glen WG, Egeghy P, Goldsmith M-R, Smith L, Vallero D, et al. SHEDS-HT: An Integrated Probabilistic Exposure Model for Prioritizing Exposures to Chemicals with Near-Field and Dietary Sources. *Environmental science & technology* 2014; 48: 12750-12759.
- Jacobs MM, Malloy TF, Tickner JA, Edwards S. Alternatives Assessment Frameworks: Research Needs for the Informed Substitution of Hazardous Chemicals. *Environ Health Perspect* 2015.
- Jacobsen RE, Fantke P, Trapp S. Analysing half-lives for pesticide dissipation in plants. *SAR and QSAR in Environmental Research* 2015; 26: 325-342.
- Jolliet O, Ernstoff AS, Csiszar SA, Fantke P. Defining Product Intake Fraction to Quantify and Compare Exposure to Consumer Products. *Environmental science & technology* 2015; 49: 8924-8931.
- Jolliet O, Fantke P. Human Toxicity. In: Hauschild MZ, Huijbregts MAJ, editors. *Life Cycle Impact Assessment*. Springer, Dordrecht, 2015, pp. 75-96.
- Judson R, Richard A, Dix DJ, Houck K, Martin M, Kavlock R, et al. The toxicity data landscape for environmental chemicals. *Environmental health perspectives* 2009; 117: 685.
- Karadzovska D, Brooks JD, Monteiro-Riviere NA, Riviere JE. Predicting skin permeability from complex vehicles. *Advanced drug delivery reviews* 2013; 65: 265-277.
- Kasting GB, Miller MA, Bhatt VD. A spreadsheet-based method for estimating the skin disposition of volatile compounds: application to N, N-diethyl-m-toluamide (DEET). *Journal of occupational and environmental hygiene* 2008; 5: 633-644.
- Kaushik G, Satya S, Naik S. Food processing a tool to pesticide residue dissipation—A review. *Food Research International* 2009; 42: 26-40.
- Keating GA, McKone TE, Gillett JW. Measured and estimated air concentrations of chloroform in showers: effects of water temperature and aerosols. *Atmospheric Environment* 1997; 31: 123-130.
- Keikotlhaile BM, Spanoghe P, Steurbaut W. Effects of food processing on pesticide residues in fruits and vegetables: a meta-analysis approach. *Food and Chemical Toxicology* 2010; 48: 1-6.
- Keil CB, Nicas M. Predicting room vapor concentrations due to spills of organic solvents. *AIHA Journal* 2003; 64: 445-454.

- Keil CB, Simmons CE, Anthony TR. Mathematical models for estimating occupational exposure to chemicals, 2nd Edition, Chapter 3.4: American Industrial Hygiene Association Press, 2009.
- Kumar D, Little JC. Characterizing the source/sink behavior of double-layer building materials. *Atmospheric Environment* 2003a; 37: 5529-5537.
- Kumar D, Little JC. Single-layer model to predict the source/sink behavior of diffusion-controlled building materials. *Environmental science & technology* 2003b; 37: 3821-3827.
- Lavoie ET, Heine LG, Holder H, Rossi MS, Lee RE, Connor EA, et al. Chemical alternatives assessment: enabling substitution to safer chemicals. *Environmental science & technology* 2010; 44: 9244-9249.
- Lee C-S, Haghighat F, Ghaly W. Conjugate mass transfer modeling for VOC source and sink behavior of porous building materials: When to apply it? *Journal of Building Physics* 2006; 30: 91-111.
- Lee CS, Haghighat F, Ghaly W. A study on VOC source and sink behavior in porous building materials—analytical model development and assessment. *Indoor Air* 2005; 15: 183-196.
- Liagkouridis I, Cousins IT, Cousins AP. Emissions and fate of brominated flame retardants in the indoor environment: A critical review of modelling approaches. *Science of the Total Environment* 2014; 491: 87-99.
- Liang Y, Liu Y, Ding Y, Liu X. Meta-analysis of food processing on pesticide residues in fruits. *Food Additives & Contaminants: Part A* 2014; 31: 1568-1573.
- Liao C, Kannan K. High levels of bisphenol A in paper currencies from several countries, and implications for dermal exposure. *Environmental science & technology* 2011; 45: 6761-6768.
- Lippmann M. Regional Deposition of Particles in the Human Respiratory Tract. *Comprehensive Physiology*, 2011, pp. 213–232.
- Little JC, Hodgson AT, Gadgil AJ. Modeling emissions of volatile organic compounds from new carpets. *Atmospheric Environment* 1994; 28: 227-234.
- Little JC, Weschler CJ, Nazaroff WW, Liu Z, Cohen Hubal EA. Rapid methods to estimate potential exposure to semivolatile organic compounds in the indoor environment. *Environmental science & technology* 2012; 46: 11171-11178.
- Liu Z, Ye W, Little JC. Predicting emissions of volatile and semivolatile organic compounds from building materials: a review. *Building and Environment* 2013; 64: 7-25.
- Lodder LCHPhd, Bremmer HJ, Engelen JGMv. ConsExpo 4.0: Cleaning Products Fact Sheet, 2006a.
- Lodder LCHPhd, Bremmer HJ, Engelen JGMv. ConsExpo: Cleaning Products Fact Sheet, 2006b.
- Lodder LCHPhd, Bremmer HJ, Pelgrom SMGJ, Park MVDZ, Engelen JGMv. ConsExpo 4.0: Disinfectant Products Fact Sheet, 2006c.
- Lorber M. Exposure of Americans to polybrominated diphenyl ethers. *Journal of Exposure Science and Environmental Epidemiology* 2007; 18: 2-19.
- Lorenz C, Hagendorfer H, von Goetz N, Kaegi R, Gehrig R, Ulrich A, et al. Nanosized aerosols from consumer sprays: experimental analysis and exposure modeling for four commercial products. *Journal of nanoparticle Research* 2011; 13: 3377-3391.
- Lu C, Fenske RA. Dermal transfer of chlorpyrifos residues from residential surfaces: comparison of hand press, hand drag, wipe, and polyurethane foam roller measurements after broadcast and aerosol pesticide applications. *Environmental health perspectives* 1999; 107: 463.
- Lu C, Schenck FJ, Pearson MA, Wong JW. Assessing children's dietary pesticide exposure: direct measurement of pesticide residues in 24-hr duplicate food samples. *Environmental health perspectives* 2010; 118: 1625-1630.
- Mackay D. Multimedia environmental models: the fugacity approach: CRC press, 2010.
- Matoba Y, Yoshimura J, Ohnishi J-i, Mikami N, Matsuo M. Development of the simulation Model InPest for Prediction of the Indoor Behavior of Pesticides. *Journal of the Air & Waste Management Association* 1998; 48: 969-978.

- McCready D. A Comparison of Screening and Refined Exposure Models for Evaluating Toluene Air Emissions from a Washing Machine. *Human and Ecological Risk Assessment: An International Journal* 2013; 19: 972-988.
- McCready D, Arnold SM, Fontaine DD. Evaluation of potential exposure to formaldehyde air emissions from a washing machine using the IAQX model. *Human and Ecological Risk Assessment: An International Journal* 2012; 18: 832-854.
- Mitragotri S, Anissimov YG, Bunge AL, Frasch HF, Guy RH, Hadgraft J, et al. Mathematical models of skin permeability: An overview. *International journal of pharmaceutics* 2011; 418: 115-129.
- Naegel A, Heisig M, Wittum G. Detailed modeling of skin penetration—an overview. *Advanced drug delivery reviews* 2013; 65: 191-207.
- Nazaroff WW. Indoor particle dynamics. *Indoor air* 2004; 14: 175-183.
- Nazaroff WW, Cass GR. Mathematical modeling of indoor aerosol dynamics. *Environmental Science & Technology* 1989; 23: 157-166.
- Nicas M. Estimating exposure intensity in an imperfectly mixed room. *American Industrial Hygiene Association Journal* 1996; 57: 542-550.
- Niino T, Asakura T, Ishibashi T, Itoh T, Sakai S, Ishiwata H, et al. A simple and reproducible testing method for dialkyl phthalate migration from polyvinyl chloride products into saliva simulant. *Shokuhin eiseigaku zasshi. Journal of the Food Hygienic Society of Japan* 2003; 44: 13-18.
- Niino T, Ishibashi T, Itoh T, Sakai S, Ishiwata H, Yamada T, et al. Comparison of Diisononyl Phthalate Migration from Polyvinyl Chloride Products into Human Saliva in Vivo and into Saliva Simulant in Vitro. *Journal of health science* 2002; 48: 277-281.
- Nougadère A, Sirot V, Kadar A, Fastier A, Truchot E, Vergnet C, et al. Total diet study on pesticide residues in France: levels in food as consumed and chronic dietary risk to consumers. *Environment international* 2012; 45: 135-150.
- NRC. A Framework to Guide Selection of Chemical Alternatives. Washington, D.C.: National Academies Press, 2014.
- Oldring P, Castle L, O'Mahony C, Dixon J. Estimates of dietary exposure to bisphenol A (BPA) from light metal packaging using food consumption and packaging usage data: a refined deterministic approach and a fully probabilistic (FACET) approach. *Food Additives & Contaminants: Part A* 2014; 31: 466-489.
- Ozak A, Gruner A, Stoermer A, Brandsch R, Franz R. Correlation between Partition Coefficients Polymer/Food Simulant, KP, F, and Octanol/Water, Log POW—a New Approach in support of Migration Modeling and Compliance Testing. *Deutsche Lebensmittel-Rundschau* 2010; 106: 203-208.
- Özer ET, Güçer Ş. Determination of di (2-ethylhexyl) phthalate migration from toys into artificial sweat by gas chromatography mass spectrometry after activated carbon enrichment. *Polymer Testing* 2012; 31: 474-480.
- Özkaynak H, Xue J, Zartarian VG, Glen G, Smith L. Modeled estimates of soil and dust ingestion rates for children. *Risk Analysis* 2011; 31: 592-608.
- Park JY, Lee K, Hwang Y, Kim JH. Determining the exposure factors of personal and home care products for exposure assessment. *Food and Chemical Toxicology* 2015; 77: 105-110.
- Pocas MF, Oliveira JC, Brandsch R, Hogg T. Analysis of mathematical models to describe the migration of additives from packaging plastics to foods. *Journal of Food Process Engineering* 2012; 35: 657-676.
- Poças MF, Oliveira JC, Oliveira FA, Hogg T. A critical survey of predictive mathematical models for migration from packaging. *Critical reviews in food science and nutrition* 2008; 48: 913-928.
- Potts RO, Guy RH. Predicting skin permeability. *Pharmaceutical research* 1992; 9: 663-669.
- Pourdeyhimi B, Ramanathan R, Javadpour S. A new carpet wear simulator. *Textile research journal* 1994; 64: 528-533.

- Prud'Homme de Lodder L, Bremmer H, van Engelen J. Cleaning Products Fact Sheet. To assess the risks for the consumer, 2006.
- Quadros ME, Marr LC. Silver nanoparticles and total aerosols emitted by nanotechnology-related consumer spray products. *Environmental science & technology* 2011; 45: 10713-10719.
- Reed KJ, Jimenez M, Freeman NC, Lioy PJ. Quantification of children's hand and mouthing activities through a videotaping methodology. *Journal of Exposure Analysis and Environmental Epidemiology* 1999; 9: 513-520.
- Rosenbaum RK, Bachmann TM, Gold LS, Huijbregts MA, Jolliet O, Juraske R, et al. USEtox—the UNEP-SETAC toxicity model: recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment. *The International Journal of Life Cycle Assessment* 2008; 13: 532-546.
- Rosenbaum RK, Meijer A, Demou E, Hellweg S, Jolliet O, Lam NL, et al. Indoor air pollutant exposure for life cycle assessment: regional health impact factors for households. *Environmental science & technology* 2015; 49: 12823-12831.
- Rothe H, Fautz R, Gerber E, Neumann L, Rettinger K, Schuh W, et al. Special aspects of cosmetic spray safety evaluations: Principles on inhalation risk assessment. *Toxicology letters* 2011; 205: 97-104.
- Sahmel J, Unice K, Scott P, Cowan D, Paustenbach D. The use of multizone models to estimate an airborne chemical contaminant generation and decay profile: Occupational exposures of hairdressers to vinyl chloride in hairspray during the 1960s and 1970s. *Risk analysis* 2009; 29: 1699-1725.
- Sanderson H, Counts JL, Stanton KL, Sedlak RI. Exposure and prioritization—human screening data and methods for high production volume chemicals in consumer products: amine oxides a case study. *Risk analysis* 2006; 26: 1637-1657.
- Schecter A, Colacino J, Haffner D, Patel K, Opel M, Pöpke O, et al. Perfluorinated compounds, polychlorinated biphenyls, and organochlorine pesticide contamination in composite food samples from Dallas, Texas, USA. *Environmental health perspectives* 2010; 118: 796-802.
- Seiler A, Bach A, Driffield M, Paseiro Losada P, Mercea P, Tosa V, et al. Correlation of foodstuffs with ethanol–water mixtures with regard to the solubility of migrants from food contact materials. *Food Additives & Contaminants: Part A* 2014; 31: 498-511.
- Shin H-M, Ernstoff A, Arnot JA, Wetmore BA, Csiszar SA, Fantke P, et al. Risk-based high-throughput chemical screening and prioritization using exposure models and in vitro bioactivity assays. *Environmental science & technology* 2015a; 49: 6760-6771.
- Shin H-M, Ernstoff AS, Arnot JA, Wetmore B, Csiszar SA, Fantke P, et al. Risk-based High-Throughput Chemical Screening and Prioritization using Exposure Models and in Vitro Bioactivity Assays. *Environmental science & technology* 2015b.
- Shin H-M, McKone TE, Bennett DH. Intake fraction for the indoor environment: a tool for prioritizing indoor chemical sources. *Environmental science & technology* 2012; 46: 10063-10072.
- Shin H-M, McKone TE, Tulse NS, Clifton MS, Bennett DH. Indoor residence times of semivolatile organic compounds: model estimation and field evaluation. *Environmental science & technology* 2013; 47: 859-867.
- Simoneau C. Applicability of generally recognised diffusion models for the estimation of specific migration in support of EU Directive 2002/72/EC. European Commission, Joint Research Centre, Institute for Health and Consumer Protection, 2010.
- Stapleton HM, Kelly SM, Allen JG, McClean MD, Webster TF. Measurement of polybrominated diphenyl ethers on hand wipes: estimating exposure from hand-to-mouth contact. *Environmental science & technology* 2008; 42: 3329-3334.
- Steiner I, Scharf L, Fiala F, Washüttl J. Migration of di-(2-ethylhexyl) phthalate from PVC child articles into saliva and saliva simulant. *Food Additives & Contaminants* 1998; 15: 812-817.

- Suciu N, Tediosi A, Ciffroy P, Altenpohl A, Brochot C, Verdonck F, et al. Potential for MERLIN-Expo, an advanced tool for higher tier exposure assessment, within the EU chemical legislative frameworks. *The Science of the total environment* 2016; 562: 474-479.
- Swanson MB, Davis GA, Kincaid LE, Schultz TW, Bartmess JE, Jones SL, et al. A screening method for ranking and scoring chemicals by potential human health and environmental impacts. *Environmental Toxicology and Chemistry* 1997; 16: 372-383.
- ten Berge W. A simple dermal absorption model: Derivation and application. *Chemosphere* 2009; 75: 1440-1445.
- ten Berge W. QSARs for skin permeation of chemicals. Jun 11, 2016.
<http://home.wxs.nl/~wtberge/qsarperm.html>.
- Tibaldi R, ten Berge W, Drolet D. Dermal absorption of chemicals: estimation by IH SkinPerm. *Journal of occupational and environmental hygiene* 2014; 11: 19-31.
- Tronde A, Nordén B, Marchner H, Wendel AK, Lennernäs H, Bengtsson UH. Pulmonary absorption rate and bioavailability of drugs in vivo in rats: structure-absorption relationships and physicochemical profiling of inhaled drugs. *Journal of pharmaceutical sciences* 2003; 92: 1216-1233.
- Trudel D, Horowitz L, Wormuth M, Scheringer M, Cousins IT, Hungerbühler K. Estimating consumer exposure to PFOS and PFOA. *Risk Analysis* 2008; 28: 251-269.
- Tusa F, Moldovan Z, Vlassa M. Identification and measurement of pesticide contaminants in food products by electron impact GC/MS. *Journal of Physics: Conference Series*. 182. IOP Publishing, 2009, pp. 012043.
- USEPA. Exposure and Fate Assessment Screening Tool (E-FAST) Version 2.0 Documentation Manual. U.S. Environmental Protection Agency, Office of Pollution Prevention and Toxics, Exposure Assessment Branch, 2007.
- USEPA. Exposure Factors Handbook 2011 Edition (Final). U.S. Environmental Protection Agency, Washington, DC, 2011.
- USEPA. Estimation Programs Interface Suite™ for Microsoft® Windows, v 4.11. United States Environmental Protection Agency, Washington, DC, 2012.
- USEPA. Consumer Exposure Model (CEM) DRAFT User Guide, 2015.
- USFDA. Guidance for Industry: Preparation of Premarket Submissions for Food Contact Substances: Chemistry Recommendations. Food and Drug Administration, Office of Food Additive Safety, College Park, MD, 2007.
- Wambaugh JF, Setzer RW, Reif DM, Gangwal S, Mitchell-Blackwood J, Arnot JA, et al. High-throughput models for exposure-based chemical prioritization in the ExpoCast project. *Environmental science & technology* 2013; 47: 8479-8488.
- Wang X, Zhang Y. General analytical mass transfer model for VOC emissions from multi-layer dry building materials with internal chemical reactions. *Chinese Science Bulletin* 2011; 56: 222-228.
- Wang X, Zhang Y, Zhao R. Study on characteristics of double surface VOC emissions from dry flat-plate building materials. *Chinese Science Bulletin* 2006; 51: 2287-2293.
- Warfield CL, Slaten BL. Upholstery fabric performance: Actual wear versus laboratory abrasion. *Textile Research Journal* 1989; 59: 201-207.
- Watkins DJ, McClean MD, Fraser AJ, Weinberg J, Stapleton HM, Sjödin A, et al. Exposure to PBDEs in the office environment: evaluating the relationships between dust, handwipes, and serum. *Environmental health perspectives* 2011; 119: 1247.
- Webster TF, Harrad S, Millette JR, Holbrook RD, Davis JM, Stapleton HM, et al. Identifying transfer mechanisms and sources of decabromodiphenyl ether (BDE 209) in indoor environments using environmental forensic microscopy. *Environmental science & technology* 2009; 43: 3067-3072.
- Wenger Y, Li D, Jolliet O. Indoor intake fraction considering surface sorption of air organic compounds for life cycle assessment. *The International Journal of Life Cycle Assessment* 2012; 17: 919-931.
- Weschler C. Roles of the human occupant in indoor chemistry. *Indoor air* 2015.

- Weschler C, Nazaroff W. SVOC exposure indoors: fresh look at dermal pathways. *Indoor air* 2012; 22: 356-377.
- Weschler CJ, Nazaroff WW. Semivolatile organic compounds in indoor environments. *Atmospheric Environment* 2008; 42: 9018-9040.
- Weschler CJ, Nazaroff WW. Dermal Uptake of Organic Vapors Commonly Found in Indoor Air. *Environmental science & technology* 2013; 48: 1230-1237.
- Wetmore BA, Wambaugh JF, Allen B, Ferguson SS, Sochaski MA, Setzer RW, et al. Incorporating High-Throughput Exposure Predictions with Dosimetry-Adjusted In Vitro Bioactivity to Inform Chemical Toxicity Testing. *Toxicological Sciences* 2015; 148: 121-136.
- Wilschut A, Wil F, Robinson PJ, McKone TE. Estimating skin permeation. The validation of five mathematical skin permeation models. *Chemosphere* 1995; 30: 1275-1296.
- Xiong J, Zhang Y, Wang X, Chang D. Macro-meso two-scale model for predicting the VOC diffusion coefficients and emission characteristics of porous building materials. *Atmospheric Environment* 2008; 42: 5278-5290.
- Xu Y, Little JC. Predicting emissions of SVOCs from polymeric materials and their interaction with airborne particles. *Environmental science & technology* 2006; 40: 456-461.
- Xu Y, Liu Z, Park J, Clausen PA, Benning JL, Little JC. Measuring and predicting the emission rate of phthalate plasticizer from vinyl flooring in a specially-designed chamber. *Environmental science & technology* 2012; 46: 12534-12541.
- Xu Y, Zhang Y. A general model for analyzing single surface VOC emission characteristics from building materials and its application. *Atmospheric Environment* 2004; 38: 113-119.
- Xue J, Zartarian V, Moya J, Freeman N, Beamer P, Black K, et al. A Meta-Analysis of Children's Hand-to-Mouth Frequency Data for Estimating Nondietary Ingestion Exposure. *Risk Analysis* 2007; 27: 411-420.
- Xue J, Zartarian V, Tulve N, Moya J, Freeman N, Auyeung W, et al. A meta-analysis of children's object-to-mouth frequency data for estimating non-dietary ingestion exposure. *Journal of Exposure Science and Environmental Epidemiology* 2010; 20: 536-545.
- Yang X, Chen Q, Zhang J, An Y, Zeng J, Shaw C. A mass transfer model for simulating VOC sorption on building materials. *Atmospheric Environment* 2001a; 35: 1291-1299.
- Yang X, Chen Q, Zhang J, Magee R, Zeng J, Shaw C. Numerical simulation of VOC emissions from dry materials. *Building and Environment* 2001b; 36: 1099-1107.
- Yeh H-C, Cuddihy RG, Phalen RF, Chang I-Y. Comparisons of calculated respiratory tract deposition of particles based on the proposed NCRP model and the new ICRP66 model. *Aerosol Science and Technology* 1996; 25: 134-140.
- Yuan H, Little JC, Marand E, Liu Z. Using fugacity to predict volatile emissions from layered materials with a clay/polymer diffusion barrier. *Atmospheric Environment* 2007; 41: 9300-9308.
- Zartarian V, Ferguson A, Leckie J. Quantified dermal activity data from a four-child pilot field study. *Journal of exposure analysis and environmental epidemiology* 1996; 7: 543-552.
- Zartarian VG, Xue J, Özkaynak H, Dang W, Glen G, Smith L, et al. A Probabilistic Arsenic Exposure Assessment for Children Who Contact CCA-Treated Playsets and Decks, Part 1: Model Methodology, Variability Results, and Model Evaluation. *Risk Analysis* 2006; 26: 515-531.
- Zhang L, Niu J. Modeling VOCs emissions in a room with a single-zone multi-component multi-layer technique. *Building and Environment* 2004; 39: 523-531.
- Zhang X, Arnot JA, Wania F. Model for screening-level assessment of near-field human exposure to neutral organic chemicals released indoors. *Environmental science & technology* 2014; 48: 12312-12319.
- Zhang X, Diamond ML, Ibarra C, Harrad S. Multimedia modeling of polybrominated diphenyl ether emissions and fate indoors. *Environmental science & technology* 2009; 43: 2845-2850.
- Zhang Z, Chen Q. Experimental measurements and numerical simulations of particle transport and distribution in ventilated rooms. *Atmospheric environment* 2006; 40: 3396-3408.

Zülch A, Piringer O. Measurement and modelling of migration from paper and board into foodstuffs and dry food simulants. Food Additives and Contaminants 2010; 27: 1306-1324.

Accepted draft